Author:
Zhu, M

Title:
Essays on sell-side analysts' non-GAAP and GAAP reporting

Essays on sell-side analysts’ non-GAAP and GAAP reporting

Mengzhu Zhu

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Abstract

This thesis seeks to assess the practical implications of equity analysts' non-GAAP and GAAP earnings reporting to different capital market participants. It consists of three essays that are presented as chapters.

The first empirical chapter uses hand collected data from analysts' reports for large European banks and examines analysts' actual and forecast GAAP and non-GAAP earnings per share (EPS). It finds that there is significant variation among sell-side analysts' non-GAAP *actual* earnings measures. These measures are not easily reconcilable to firms' reported non-GAAP earnings, GAAP earnings or to street earnings reported by I/B/E/S. By contrast, reported measures of GAAP earnings in analysts' reports rarely differ from one another or from firms' reported GAAP earnings. When evaluated against analysts' own actual non-GAAP earnings measures, forecasts appear more accurate and more biased than those based on I/B/E/S. This chapter suggests that although non-GAAP earnings measures are more persistent, GAAP earnings are less vulnerable to measurement ambiguity across analysts. Therefore, whether non-GAAP or GAAP earnings are superior involves a trade-off of persistence and measurement uncertainty.

The second empirical chapter studies the relative informativeness at the earnings announcement date and post earnings announcement drift (PEAD) associated with GAAP and non-GAAP earnings surprises. Previous studies misalign GAAP actual earnings with non-GAAP forecasts to measure GAAP earnings surprises. This chapter overcomes this measurement error problem by aligning the measurement bases of both forecast and actual GAAP earnings. It finds that investors still perceive non-GAAP earnings to be more informative than GAAP earnings at the earnings announcement date. However, previously identified GAAP earnings surprises downwardly bias market responses to GAAP earnings. In addition, after correcting the measurement error, the evidence suggests that the GAAP-based PEAD is higher than the non-GAAP based PEAD, indicating that investors may not use the information contained in GAAP earnings as efficient as non-GAAP earnings.

The third empirical chapter explores analysts' disagreement on GAAP earnings forecasts, forecast exclusions and their relationship with future stock returns. In this chapter, the non-

GAAP forecasts are separated into two components: GAAP forecasts and forecast exclusions. It finds that both analysts' disagreement on non-GAAP forecasts and disagreement on GAAP forecasts are negatively associated with future stock returns. However, a higher level of disagreement on forecast exclusions is associated with higher future stock return. Further evidence suggests that dispersion in forecast exclusions reflects the firm idiosyncratic risk and the uncertainty of fundamental firm value.

Overall, the thesis extends the literature on analysts' non-GAAP reporting by demonstrating that analysts disagree significantly on how actual non-GAAP earnings are measured. It also complements the literature on market reactions to analysts' forecasts and the literature on analyst dispersion anomaly by provides additional evidence on the implications of analysts' GAAP forecasts and forecast exclusions for capital market participants.

Declaration

I declare that the work in this thesis was carried out in accordance with the requirements of the University's *Regulations and Code of Practice for Research Degree Programmes* and that it has not been submitted for any other academic award. Except where indicated by specific reference in the text, the work is the candidate's own work. Chapter 2 is a joint work in collaboration with, and with the assistance of Professor Mark Clatworthy and Doctor Tuan Ho. Any views expressed in the thesis are those of the author.

SIGNED: DATE:

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Chapter 1

Introduction

1.1 Motivation

Sell-side analysts act as a link between investors and companies as well as influencing the trajectory of the market (Clatworthy and Lee, 2018– e.g. on impact of forecast revisions on the market). The earnings measures generated and used by analysts are often considered to be the archetypal non-GAAP or street earnings (e.g. Baik et al., 2009; Bradshaw et al, 2018b). Because analysts can decide which components of GAAP earnings are to be excluded based on their own judgements (Baik et al., 2009) and they may face conflicts of interests that may bias their earnings measures, (Michaely and Womack, 1999; Kadan et al., 2009), more attention is being paid by researchers to the treatment of non-recurring items by analysts (e.g. Bratten et al., 2020). Such research seeks to assess the nature and consequences of analysts' non-GAAP and GAAP earnings measures. Despite such research, the measurement of earnings by analysts remains poorly understood.

The current thesis addresses the following issues, aiming to improve our understanding of analysts' earnings measures and their capital market consequences: (i) analysts' disagreement surrounding non-GAAP earnings measures and how this affects inferences on analysts' forecast rationality and overreaction; (ii) how the stock market reacts to non-GAAP and GAAP earnings surprises, and (iii) the links between analysts' disagreement on earnings forecasts and future stock returns.

Regarding the first issue, prior research typically measures analysts' expectations and earnings outcomes using I/B/E/S data as a proxy for non-GAAP earnings (e.g. Bradshaw and Sloan, 2002; Bhattacharya et al., 2003). For each firm year or firm quarter, I/B/E/S provides one single actual earnings figure based on a 'majority rule', where the respective earnings figure is meant to represent the definition that most analysts agree on (see I/B/E/S, 2015). However, Brown and Larocque (2013) challenge this notion by introducing a method of inferring individual analysts' actual earnings. They find that analysts' measures often differ from I/B/E/S reported figures. They show that quarterly actual earnings provided by I/B/E/S can differ from inferred actual earnings up to 50% of the time, and that failure to recognize this phenomenon may understate the accuracy of analysts' forecasts and result in erroneous inferences. Bradshaw et al. (2018a) further compare the differences in the properties of analysts' forecasts between forecasts recorded in I/B/E/S and forecasts provided by Thomson Reuters. They conclude that the latter are more accurate and less biased. Nevertheless, little attention has been devoted to the *actual* earnings reported in analysts' reports, or how they relate to the same individual analyst's previous forecasts. As noted by Bratten et al. (2020), observed differences in analysts' forecasts may represent not just differences in expected performance, but also differences in the way that performance is measured by different analysts. Thus, Chapter 2 investigates the variation across individual analysts in the treatment of excluding items. My study therefore differs from prior research by focusing not only on analysts' earnings *forecasts*, but also their *actual earnings realisations*.

In terms of the second issue, due to the lack of availability of GAAP forecast data before 2004, the properties of analysts' GAAP forecasts are based on the difference between GAAP actuals and non-GAAP forecasts on I/B/E/S (Lougee and Marquardt, 2004; Black and Christensen, 2009). This creates a measurement error that misaligns GAAP actual earnings with non-GAAP forecasts. The measurement error problem has been identified as a major limitation that may have contaminated previous results (Lambert, 2004; Cohen et al., 2007; Helflin and Hsu, 2008). Consequently, Chapter 3 studies the short- and long-term market reactions to GAAP and non-GAAP earnings using 'corrected' measures of GAAP earnings surprises. In addition, the availability of GAAP forecast data allows me to study the relationship between stock returns and dispersion in analysts' GAAP forecasts in Chapter 4. As analysts generally have more freedom in adjusting non-GAAP numbers, the dispersion in their non-GAAP forecasts may be influenced analysts' unique incentive structure. For instance, they may choose to converge to – or depart from - the consensus forecast number because of career concerns. The recent study by Bratten et al. (2020) reports that the variation in analysts' forecast exclusions is associated with opportunism. This issue could partially be addressed by exploring the dispersion in analysts' GAAP forecasts and dispersion in analysts' forecast exclusions separately.

1.2 Contribution

This thesis contributes to four streams of literature. Chapter 2 extends the literature on sell-side financial analysts' earnings forecasts by demonstrating that analysts disagree significantly on how actual non-GAAP earnings are measured. Prior studies use a single earnings outcome provided by I/B/E/S to represent actual non-GAAP or 'street' earnings measures. This approach fails to reflect the significant variation in the treatment of excluding items by individual analysts in actual earnings realisations. In short, street earnings are variable, not constant, as assumed by many prior studies. I further show that using analysts' own definition of actual earnings can change inferences of the properties of their forecasts. In contrast, GAAP earnings definitions are generally highly consistent across analysts, making them more suitable for performing the 'disciplining role' in evaluating analysts' forecasts.

Second, chapter 2 contributes to the non-GAAP literature building on the analysis of Bentley et al. (2018), who find that analysts' definitions of non-GAAP earnings often differ from those of managers. I show that analysts often disagree amongst themselves about how non-GAAP earnings are measured and that these differences are not easily reconcilable to those reported by forecast data providers.

Third, chapter 3 contributes to the long line of literature of market reactions to analysts' forecasts. Due to the lack of availability of GAAP earnings forecast data before 2004, prior studies of the market reactions to different earnings definitions define GAAP earnings surprise as the difference between GAAP actual earnings and non-GAAP forecasts, which may give rise to substantial measurement errors (Berger, 2005; Cohen et al., 2007, Bradshaw et al., 2018b). After correcting this measurement error by aligning the measurement bases of both forecast and actual earnings, I reassess the short- and long-term market reactions to different definitions of earnings in an international setting in Chapter 3. I show that previously identified GAAP earnings surprises downwardly bias market responses to GAAP earnings. The error component (i.e., forecast exclusions) provide incrementally useful information, in addition to the information found in GAAP forecasts. In terms of longer run reactions to earnings surprises, I show that investors may not use the information contained in GAAP earnings as efficiently as non-GAAP earnings.

Finally, Chapter 4 contributes the literature on the analyst dispersion anomaly and analysts' non-GAAP reporting. I provide further evidence on the role of dispersion in analyst' GAAP forecasts and dispersion in forecast exclusions in predicting the cross-sectional future returns. I show that the dispersion in analysts' GAAP forecasts is negatively associated with future stock returns. However, the levels of disagreement on exclusions from GAAP forecasts are positively associated with future stock return. Bratten et al. (2020) investigate individual analysts' forecast exclusions and find that analysts' exclusion behaviours are associated with opportunism. My study complements this by exploring whether and how investors respond to different opinions among analysts' exclusions forecasts.

Overall, my research indicates that although non-GAAP earnings measures are more persistent, the disagreement across analysts about how performance is measured introduces an additional dimension of uncertainty that GAAP earnings to not suffer from. Whether non-

GAAP or GAAP earnings are superior involves a trade-off of persistence and measurement uncertainty. In addition, my research provides additional evidence on the implications of analysts' GAAP forecasts and forecast exclusions for capital market participants.

1.3 Thesis Structure

The remainder of the thesis includes three self-contained chapters and a concluding chapter. Chapter 2 investigates analysts' disagreement about the past non-GAAP earnings measures (actual non-GAAP EPS) and its impact on evaluation of individual analysts' non-GAAP forecasts. Chapter 3 examines the relative informativeness and post earnings announcement drift (PEAD) for GAAP and non-GAAP earnings. Chapter 4 studies the dispersion in analysts' GAAP forecasts, exclusions forecasts and their relationship with future stock return. Chapter 5 concludes with a summary of my main findings, an acknowledgement of the limitations of the research and some brief suggested directions for future research.

Chapter 2

Disagreement about the Past: An Empirical Assessment of Bank Analysts' Non- GAAP Earnings Measures

Abstract

Prior research documents that analysts' 'street earnings' exclude transitory items in order to facilitate security valuation. Based on an examination of analysts' reports for large European banks, I document significant variation in sell side analysts' non-GAAP actual (as opposed to forecast) earnings measures. These measures are not easily reconcilable to firms reported non-GAAP earnings, GAAP earnings or to street earnings reported by I/B/E/S. By contrast, reported measures of GAAP earnings in analysts' reports rarely differ from one another or from firms' reported GAAP earnings. When evaluated against analysts' own actual non-GAAP earnings measures, forecasts appear more accurate and more biased than those based on I/B/E/S. Results for GAAP earnings are less conclusive. My results show that as well as disagreeing about future earnings, analysts also disagree significantly about what earnings were in the past.

2.1 Introduction

One of the primary functions of accounting information in capital markets is to confirm prior expectational information (Gigler and Hemmer, 1999). This ‘disciplining’ role of accounting is meant to enhance the accountability of managers and other information providers through an agreed-upon system of measurement whereby outcomes of previous forecasts of corporate performance can be evaluated ex post (Ball and Shivakumar, 2008). Regulators and standard setters view the recent proliferation of non-GAAP reporting as a significant threat to this role (e.g. Young, 2014; Guillamon-Saurin et al., 2017; Black et al., 2018).

Non-GAAP (or pro-forma or underlying) earnings measures are argued to be superior for predictive purposes because they exclude transitory or non-recurring items. Accordingly, investors find non-GAAP measures more informative than GAAP measures (e.g. Bradshaw and Sloan, 2002; Gu and Chen, 2004). At the same time, the managerial discretion involved in preparing non-GAAP measures has led to concerns of managerial opportunism. Non-GAAP earnings are routinely higher than GAAP earnings (e.g., Leung and Veenman, 2018) and managers may select measures to meet targets and beat analyst expectations (Doyle et al., 2013), rather than to communicate companies’ true underlying performance.

Prior research typically measures analysts’ expectations and earnings outcomes using I/B/E/S data as a proxy for ‘street’ earnings. Much of what we know about the properties of analysts’ forecasts is based on I/B/E/S forecast and actual earnings per share (EPS) data, typically measured on a non-GAAP basis. In this chapter, I show that a single reported ‘street’ earnings figure for a given company in a given period can mask significant underlying variation among equity analysts in how actual earnings outcomes are measured. I/B/E/S and other data providers recognize that measurement rules may differ between analysts when they supply earnings forecasts, so they adopt a 'majority rule', where the respective earnings figure is meant to represent the definition that most analysts were forecasting at the time (Gu and Chen, 2004). Based on earnings figures taken from a sample of analysts' reports for European banks, my evidence suggests that this process can be difficult to operationalize and that 'street' earnings is variable, not constant. Although it is widely recognised in the literature that analysts disagree about what earnings will be in the future, there has been limited appreciation of the extent to which they disagree about what firms' earnings were in the past. After documenting substantial variation across analysts in the measurement of actual earnings, I assume that analysts themselves are best placed to ensure consistency in the measurement rules used in preparing their forecast and reported earnings. This enables us to examine whether the application of consistent measurement rules affects the properties of analysts' forecast accuracy, bias and efficiency.

This study is not the first to examine analysts' actual earnings measurement practices. Brown and Laroque (2013) introduce a method of inferring actual earnings and find that these often differ from I/B/E/S reported figures. They show that quarterly actual earnings provided by I/B/E/S can differ from inferred actual earnings up to 50% of the time, and that failure to recognize this phenomenon may understate the accuracy of analysts' forecasts and result in erroneous inferences. Although they infer analyst actuals, Brown and Laroque (2013) do not study the actual earnings figures reported by analysts themselves in their research reports. Bradshaw et al. (2018b) find that analysts' forecasts provided by Thomson Reuters via their analysts' reports service are more accurate and less biased than other I/B/E/S forecasts. However, although Bradshaw et al. (2018b) focus on differences in the properties of analysts' forecasts, they nevertheless employ I/B/E/S actual earnings outcomes in their analysis.

In a major recent development in the analyst forecast literature, Bradshaw et al.

(2018b) show that the subjectivity in the measurement of analysts' non-GAAP earnings forecasts can be mitigated through the use of GAAP earnings forecasts. They find that investors still respond more to non-GAAP earnings than GAAP earnings, but they report that analysts' GAAP earnings forecasts can be useful to investors by increasing the credibility of non-GAAP earnings metrics. This study builds on this literature by examining the variation in both GAAP and non-GAAP earnings measures across analysts.

To study the levels of (dis)agreement across analysts in measuring actual earnings, I focus on equity analysts' reports on European banks. Due to their scale and the nature of their activities in monitoring, financial intermediation and supplying credit, banks play a particularly important role in market economies. The majority of empirical accounting research tends to focus on banks' balance sheets and asset/liability composition, rather than their income statements, on the grounds that these are used as the basis for prudential regulatory calculations, such as leverage and capital adequacy ratios (Beatty and Liao, 2014).[1] Nevertheless, the income statement remains relevant in this context due to the importance of retained earnings in constituting equity for regulatory purposes. In addition, the scale of the European banking sector means that banks are heavily represented in investors' portfolios, so the valuation of their quoted securities – which typically requires performance-based information – remains important as well.

Because they hold non-traded assets (i.e., non-marketable loans), and routinely use financial instruments (particularly derivatives) in their hedging and trading activities, banks are informationally opaque (Beatty and Liao, 2014)[2] and are often complex to analyze and evaluate, even for experienced analysts (Chang et al., 2016) and auditors (Bratten et al., 2019). This complexity makes analysts' measurement of banks' earnings inherently

[1] An exception is the large literature that examines banks' loan loss provisioning, which focuses only on a subset of the income statement.
[2] Indeed, Beatty and Liao (2014) discuss the literature showing that banks' main role makes them *optimally* opaque (Dang et al., 2017).

challenging. In addition to the innate complexity and opaqueness of banks, there are often substantial items in European banks' income statements that analysts may find difficult to classify as either recurring or non-recurring. In several controversies, including the LIBOR scandal the mis-selling of interest rate swaps and payment protection insurance, EU banks have incurred significant regulatory penalties, leading to large financial settlements.[3] Many banks' earnings have recently included charges running into hundreds of millions of pounds. Determining whether such items should feature in analysts' forecast and actual earnings is ultimately a subjective judgement, which may lead to different treatments across analysts. My focus on European banks reflects the less regulated nature of the non-GAAP reporting environment relative to the US (e.g. Guillamon-Saurin et al., 2017).

I contribute to two streams of literature. First, I contribute to the literature on financial analysts by showing that analysts' 'street earnings' are not well defined. Analysts disagree significantly and often about how actual earnings are measured, and these differences can affect the evaluation of individual analysts' non-GAAP forecasts. In contrast, GAAP earnings definitions are generally highly consistent across analysts (and correspond closely to those reported by companies). This leads to a trade-off: although GAAP earnings are potentially contaminated by transitory items, they are also less prone to changes in definition ex post. This makes them more suitable for performing the disciplining role in forecast evaluation. Second, I contribute to the non-GAAP literature by building on the analysis of Bentley et al. (2018), who find that analysts' definitions of non-GAAP earnings often differ from those of managers. My analysis shows that analysts often disagree amongst themselves about how non-GAAP earnings are measured and that these differences are not easily reconcilable to those reported by forecast data providers.

[3] For example, the FT (August 30th, 2019) points out: "[In the two decades beginning in the late 1990s], Lloyds has put aside £20bn to settle potential mis-selling claims, topping a list of UK lenders who collectively expect the PPI scandal to cost them close to £50bn." https://www.ft.com/content/2abb8482-c9b3-11e9-a1f4-3669401ba76f

Despite the importance of banks and the relative lack of research on their income statements, I recognize that my findings may not generalize to the non-financial corporate sector. Moreover, earnings per share is not the only metric used in the evaluation of banks' financial position and performance. In particular, regulatory capital and leverage are often used to assess the financial status of banks (e.g. Beattie and Liao, 2014). Nevertheless, I expect earnings to remain an important metric to evaluate bank performance in equity markets.

In the next section, I first provide a brief overview of the literature on non-GAAP earnings measures as reported by managers and as used by analysts. I then outline my data and sample in section 2.3. My main findings follow in section 2.4, while section 2.5 concludes.

2.2 Companies' and Analysts' Non-GAAP Earnings Measures

In a recent and comprehensive review of the literature, Black et al. (2018) document a proliferation in non-GAAP reporting in the last two decades. They report that a large amount of evidence supports the idea that non-GAAP figures are informative to capital market participants, and several studies (e.g. Bradshaw and Sloan, 2002; Bhattacharya et al., 2003) show non-GAAP earnings measures are often more useful than GAAP earnings for security valuation. While this evidence supports an information, rather than an opportunistic role, for non-GAAP earnings, such measures can also be reported with more strategic aims, (e.g. by excluding recurring expenses), so that they are biased upwards. This has led some to see non-GAAP reporting as a threat to the integrity of the GAAP financial reporting system (e.g. Black et al., 2018; Young, 2014). However, GuillamonSaurin et al. (2017) suggest that investors are aware of the potential for biased non-GAAP communication by managers and discount it when it is too aggressive.

Until recently, researchers treated the non-GAAP earnings figures produced by managers as equivalent to those produced by analysts, proxied by I/B/E/S data. But Bentley et al. (2018) show that although managers' and analysts' non-GAAP figures overlap, they are not always the same. In particular, I/B/E/S data exclude manager's low-quality adjustments and thus underestimate the aggressiveness of managers' reporting. What is less well understood from existing evidence is the extent to which I/B/E/S data fully represents the non-GAAP measurement and adjustment processes of analysts.

In a recent study, Bradshaw et al. (2018a) document that the properties of earnings forecasts vary according to the channel used to disseminate the research. Based on a large sample of US companies, they find that analysts' forecasts distributed via a premium channel (i.e., via research reports distributed through Thomson Reuters Research) are less biased and more accurate than those sent through the 'standard channel' of I/B/E/S. In their analysis, accuracy and bias are measured as the difference between analysts' forecasts (as reported in research reports) and I/B/E/S actual earnings. Interestingly, they document significant variation in dissemination arrangements, where different clients have different levels of access (e.g., different metrics, different time delays and differences in access to data) depending on contractual terms and restrictions on availability imposed by contributing brokers.

A distinguishing feature of I/B/E/S data – both GAAP and non-GAAP – is that actual earnings per share are constant for each firm-year (or quarter). According to I/B/E/S, company actual figures are collected from multiple newswire feeds, press releases, company websites and public filings. While prior research contends that the I/B/E/S definitions of forecast EPS and actual EPS measures are consistent (e.g. Capstaff et al., 2001), little is known about how the data are actually compiled.

In an assessment of inclusions and exclusions made by analysts as part of the First

Call database (which has subsequently been acquired by Thomson Financial, the then owner of I/B/E/S), Gu and Chen (2004) find that included items are more persistent and have higher valuation multiples than exclusion items, suggesting that ‘street’ earnings are of higher quality than GAAP earnings. Recognizing that analysts vary in their treatment of recurring items, they report that exclusions are typically made on a ‘majority rule’ basis and point out (2004, p. 133) that earnings exclusion decisions are complex and *ad hoc*, with a risk that analysts may choose an earnings figure that provides the closest match to their forecasts.

Because analysts may make numerous adjustments to earnings at different stages in the forecasting cycle, it is likely to be very difficult for forecast data providers to distil corporate performance measures across multiple analysts into a single measure. Hence, a single earnings outcome may fail to reflect the variation in the treatment of non-recurring items by individual analysts, not just in earnings forecasts, but also in realisations. As pointed out by Brown and Laroque (2013), I/B/E/S data are often used to judge the accuracy and bias of analysts’ forecast ex post, yet a failure to recognize that I/B/E/S figures do not always represent those analysts were using when issuing their forecasts may result in unreliable inferences.

Because of the limited existing empirical evidence in this area, my aims are partly exploratory. Building on prior literature on the properties of analysts’ forecasts and ‘street’ earnings, I study the actual earnings per share data reported by individual analysts in their research reports, and compare these figures across analysts and to those recorded by I/B/E/S. My first research question is:

RQ2.1: To what extent do analysts’ non-GAAP actual earnings figures differ from each other and those reported by I/B/E/S?

With the exception of Bradshaw et al. (2018b), prior research on analysts’ forecasts focuses on non-GAAP earnings measures, treating them as a surrogate for ‘street’ earnings.

Because the non-GAAP earnings measures may not be well-defined – even ex post – the extent to which earnings can indeed perform a disciplining role for other information sources is unclear. This role may be better suited to GAAP measures, although there is limited understanding of the extent to which analysts' earnings measures conform precisely to those prepared under a strict GAAP regime. To investigate the disciplining role of the audited GAAP regime in confirming analysts' forecasts, I am therefore also interested in the comparative variation across analysts in GAAP actual earnings figures. My second research question is:

RQ2.2: To what extent do analysts' GAAP actual earnings figures differ from each other and those reported by I/B/E/S?

After documenting that there is significant variation across analysts and between analysts and I/B/E/S for non-GAAP earnings, but limited variation for GAAP earnings, I match the forecasts and actual earnings across research reports produced by the same analysts to evaluate whether using analysts' own definition of actual earnings changes inferences of the properties of their forecasts. My final research question is therefore:

RQ2.3: Does using analysts' own actual earnings figures change inferences of the properties of their forecasts compared with I/B/E/S data?

2.3 Data and Sample

2.3.1 Data

I obtain a sample of analysts' reported actual and forecast EPS from analysts' reports taken from Investext. Because this study is intended to investigate the ways in which analysts cope with complex and opaque companies' reporting items that may be hard to classify, I select a sample of 4 large UK banks and 5 European banks from the STOXX600 index and collect a sample of analysts' reports for them over the period 2010 to 2017. In order to keep the data collection task manageable and to focus on analysts' forecasts around the earnings announcement date, I restrict my sample to analysts' reports issued 60 days before and 60 days after the earnings announcement date for each bank.

From the reports, I record information the earnings announcement date, broker name, analysts' names, stock price, price target, recommendation, analyst report date, description of GAAP EPS and non-GAAP EPS, actual EPS reported for the previous fiscal year (FY0) and the year before previous fiscal year (FY-1), as well as forecast EPS reported for the current fiscal year (FY1) and for the next fiscal year (FY2).

Figure 2.1 presents the timeline for the data collection process, taking Barclays' earnings announcement date of 23/02/2017 as an example. In this example, for analysts' reports issued 60 days before 23/02/2017, I record actual EPS for 2014 and 2015, and forecast EPS for 2016 and 2017. For analysts' reports issued 60 days after 23/02/2017, I record actual EPS for 2015 and 2016, and forecast EPS for 2017 and 2018.

Insert Figure 2.1 about here

I identify the current fiscal year according to each analyst report as they indicate "A" next to the year headings for previous years to indicate actual EPS, and "F" or "E" for the current fiscal year to represent forecast or expected EPS. EPS actual and EPS forecasts are typically obtained from the first page of analysts' reports, which supports the idea that EPS is an important performance metric for the banks in this study. In the rare cases where EPS figures do not appear on the first page of the report, I obtain them from the financial summary chart elsewhere in the report. GAAP EPS is reported as 'Reported EPS', 'EPS (stated)' and 'Statutory EPS' in analysts' reports, whereas non-GAAP EPS is reported as 'Adjusted EPS' or 'Underlying EPS'.

Once all reports are collected, I manually adjust the EPS actuals, forecasts and share prices where there are stock splits in order to ensure consistency through time and with the

I/B/E/S adjusted data. Specifically, I adjust the relevant data for Royal Bank of Scotland (RBS) for its one-for-ten consolidation of ordinary shares, which took effect in June 2012. I use the ratio of the company restated EPS to the company reported EPS before restatement as the adjustment factor. For a subsample of analysts' reports, I also collect data on reconciliations between GAAP and non- GAAP data, where available.

For comparative purposes, I obtain both non-GAAP and GAAP EPS measures from the *Detailed History* I/B/E/S files from WRDS. GAAP EPS figures have been available on I/B/E/S since 2004 (Bradshaw et al., 2018b). To be consistent with the hand-collected data, I require the I/B/E/S forecasts to be issued between 60 days before and 60 days after the earnings announcement date. Each I/B/E/S EPS forecast is matched to the I/B/E/S stock price from the month before the forecast date for scaling purposes.

2.3.2 Sample

My initial hand-collected sample comprises 1,362 analysts' reports for 9 European banks. In 47 cases, analysts report their forecast EPS after the earnings announcement date. I exclude these, which reduces the sample to 1,315 reports. Because I can sometimes obtain more than one figure from each report, the final hand-collected sample comprises 2,021 analysts reported non-GAAP actual EPS figures, 1,842 analyst reported GAAP actual EPS figures, 1,209 non-GAAP forecasts and 1,105 GAAP forecasts for the next accounting year. The data collected from I/B/E/S comprises 2,924 non-GAAP forecasts, 1,961 GAAP forecasts, 81 GAAP actual EPS figures and 81 non-GAAP actual EPS figures.

The focus here is principally on the disagreement between analysts on the measurement of GAAP and non-GAAP actual EPS. When assessing this, it is important to examine the extent to which analysts report reconciliations between the two measures. This is because any variation in non-GAAP measurement can be overcome via adjustments by users of analysts' reports. To explore this issue, I hand collect detailed reconciliations in annual reports and analysts reports from between 2010 and 2013.

Analysts' reports are divided into three categories: no reconciliation, limited reconciliation, and detailed reconciliation. Analysts' reports are considered as 'no reconciliation' if no information on GAAP and Non-GAAP reconciliations can be found in the reports. In some cases, the reports contain a limited reconciliation, including items such as 'Other exceptionals' and 'Goodwill impairment'; however, the information in these cases does not allow clear identification of which items are excluded from GAAP net income to arrive at the non-GAAP actual EPS. In other cases, a detailed reconciliation is disclosed in the reports.[4] Because analysts' ability to supply detailed reconciliations may depend on the disclosure level of the banks they are following, I also report results by bank disclosure levels.[5]

Table 2.1 reports the descriptive statistics for the GAAP and non-GAAP reconciliations. Overall, almost half of the analyst reports contain no reconciliations at all. This suggests that for a significant proportion of analyst reports, it is not possible to fully ascertain what adjustments are being made to GAAP EPS to arrive at the non-GAAP measures. When banks provide GAAP and non-GAAP reconciliations in their annual reports, analysts seem more likely to provide detailed reconciliations than when banks do not provide them (22.30% versus 12.82%). The likelihood of analysts not providing GAAP and non-GAAP reconciliations is also higher when banks do not provide reconciliation information (55.13% versus 46.71%). Nevertheless, a chi-squared test (not reported in the table) indicates that the differences are not significant (p = 0.147).

Insert Table 2.1 about here

[4] Examples of excluded items in these detailed reconciliations include 'Own credit spread', 'Acquisitions, disposals & dilutions', 'UK customer redress programs', 'fines & penalties', 'UK pension credit', 'Restructuring & other related costs'.

[5] Two banks do not provide any reconciliations during this period.

2.4 Results

2.4.1 Differences between analysts' EPS and I/B/E/S actual EPS

Since I/B/E/S reports only one actual earnings figure based on the majority rule, and because it is often used to represent 'street earnings', I begin by using I/B/E/S EPS as a benchmark to investigate the consistency of analysts' actual earnings figures. If actual earnings measurements are consistent across analysts and are well-represented by the I/B/E/S figures, I should find that the difference between analysts' actual EPS and I/B/E/S reported number is insignificantly different from zero and that there is limited variation around the mean for analysts' own EPS. Prior to presenting the results of the empirical analysis, I provide an example to illustrate the degree of variations in analysts' non-GAAP actual earnings and how these figures differ from those reported by I/B/E/S.

I select HSBC for this illustration – a bank which reports the use of non-GAAP measures and provides a reconciliation of non-GAAP financial measures for the 2012 and 2011 fiscal year (HSBC, 2012, p.24-28). In 2012, HSBC reports GAAP EPS of \$0.74, 20% lower than for the previous year (\$0.92), while dividends per share increase from \$0.39 in 2011 to \$0.41 in 2012 and the Tier 1 ratio improves from 11.5% to 13.4%. I/B/E/S reports non-GAAP EPS for HSBC in 2012 as \$0.74, the same as the GAAP EPS in the HSBC annual report. This implies no significant adjustments were made by analysts. In contrast, using data from analysts' reports on HSBC collected from within 30 days after the earnings announcement date, I find significant variation in analysts' actual non-GAAP EPS.

Table 2.2, Panel A reports individual analysts' actual GAAP and non-GAAP EPS. Column (3) of Table 2.2 presents the various GAAP EPS measures, while column (4) shows non-GAAP EPS. Actual non-GAAP EPS ranges from \$0.76 (UBS) to \$1.94 (Deutsche Bank). This is important to note that the average of these figures deviate significantly from the I/B/E/S actual non-GAAP EPS. The average of these figures is \$1.003, 35% higher than the I/B/E/S figure of $0.74. Indeed, none of the non-GAAP EPS figures in the sample corresponds to the I/B/E/S figure. Even if I remove the Deutsche Bank observation as an outlier, the average actual non-GAAP EPS is still significantly higher than the I/B/E/S figure ($0.88 versus $0.74, or 18.9% higher). In other words, analysts' actual non-GAAP EPS differs significantly from I/B/E/S actual non-GAAP EPS, as well as from firm reported EPS. I do not observe such a pattern for GAAP EPS. Most of the analysts' report a GAAP EPS very close to (or equal to) $0.74.

To investigate the sources of the disagreement across analysts, I explore what adjustments create the disagreement in actual non-GAAP EPS figures. Table 2.2, Panel B presents the detailed reconciliation of GAAP net profits and non-GAAP adjusted net profits (pre- and after tax) based on data collected from analysts' reports. Analysts' major adjustments include fair value movements arising from changes in own credit spreads, acquisitions, disposals and dilutions, regulatory related charges (UK customer redress programs, US fines & penalties, UK pension credit), and restructuring costs. There are also smaller adjustments, such as non-qualifying hedges and gains/losses on sales of Ping An business in China and non-core investment in India.

Insert Table 2.2 about here

While analysts tend to agree highly on adjustments related to fair value movements arising from changes in own credit spreads, they disagree about regulatory-related charges and the gains/losses on sales of businesses. The outlier of Deutsche Bank can be explained by an abnormally high adjustment of extraordinary and other items. These figures show how it can be extremely difficult to apply one majority rule, as outlined by I/B/E/S, in this situation. There seems to be no clear majority view regarding which items to be adjusted, or the appropriate value of the adjustments.

2.4.2 Descriptive Statistics

Table 2.3 present the summary statistics of the differences between the non-GAAP actual EPS obtained from analysts' reports and those from I/B/E/S across the nine banks in the sample. I scale the differences between analysts' EPS and I/B/E/S EPS by the stock price reported in analysts' reports, which are the most recent stock prices available before analysts write their reports.

Insert Table 2.3 about here

Table 2.3 shows that the mean and median difference between non-GAAP actual EPS obtained from analysts' reports and I/B/E/S actual EPS (DIFFACT_P) are significantly different from zero. The standard deviation of 0.099 also points to significant variations around the mean for most banks. Comparing with the case of GAAP EPS, the mean of DIFFACT_P in the non-GAAP EPS sample is 4 times higher (0.0458 compared to 0.0136) and the standard deviation is around twice as high (0.099 compared to 0.053). The median of DIFFACT_P for GAAP EPS is very close to zero, suggesting a high level of agreement between analysts. However, I still observe a significant level of disagreement (almost 2 percent of stock price for non-GAAP EPS). In other words, there is considerable disagreement between analysts about past non-GAAP EPS, while there some limited disagreement for GAAP EPS. The average actual GAAP EPS obtained from analyst reports is much closer to the I/B/E/S actual GAAP EPS, while the average actual non-GAAP EPS obtained from analyst reports deviates significantly -and often - from I/B/E/S figures.

2.4.3 Bank fixed effect regressions

I complement the summary statistics of Table 2.3 with a regression analysis where I regress the differences between the actual EPS obtained from analysts' reports and from I/B/E/S on bank fixed effects. If analysts consistently apply similar adjustments to actual non-GAAP

EPS across banks, I should find that most of the coefficients on bank dummy variables, including the constant term which captures the baseline bank, are insignificantly different from zero.

Insert Table 2.4 about here

Panel A of Table 2.4 reports the results from regressing analyst-I/B/E/S differences in non-GAAP actual EPS on bank fixed effects, while Panel B shows the results for GAAP actual EPS. Colum (1) reports the results scaled by stock prices, while column (2) presents results for differences deflated by the absolute value of I/B/E/S EPS. The coefficients for most banks in Table 2.4, Panel A are significantly different from zero, and the constant term is significantly positive in both columns. Barclays is (arbitrarily) chosen as the baseline bank in this analysis. The coefficients on KBC and the constant term are significantly positive, confirming that, on average, analysts tend to issue non-GAAP actual EPS figures higher than I/B/E/S figure for these banks. The other coefficients are all significantly negative, and most of them are significantly larger (in absolute terms) than the constant term, implying that on average, these banks tend to be associated with analysts' non-GAAP actual EPS below the I/B/E/S figure. These statistics confirm the findings from Table 2.3 that analysts' actual non-GAAP EPS measures deviate significantly from I/B/E/S non-GAAP actuals.

In contrast to the (non-GAAP) results in Panel A of Table 2.4, Panel B (GAAP EPS) shows that most of the coefficients on bank fixed effects are insignificantly different from zero, including the constant term. The exceptions are Deutsche Bank, KBC and Royal Bank of Scotland (RBS). For RBS, the difference is significant at the 10 percent level, while the significance (and sign for KBC) depends on the scaling variable used. These statistics also confirm the findings from Table 2.3 that analysts are far more consistent when reporting the GAAP actual EPS, leading to fewer departures from I/B/E/S actual numbers.

Overall, the results in Tables 2 - 4 indicate that the GAAP reporting regime leads to much higher consistency between analysts in their measurement of actual GAAP EPS, illustrating the disciplining role of the audited GAAP regime. By contrast, the non-GAAP reporting regime allows more discretion for individual analysts, there is significant disagreement about banks' past performance, and these figures are not easily reconcilable to GAAP figures in a large number of cases.

2.4.4 Broker fixed effect regressions

I next examine the extent to which broker fixed effects explain analyst-I/B/E/S differences in actual EPS. This analysis investigates the possibility that brokerage firms have certain preferences for particular non-GAAP adjustments. As a result, their non-GAAP actual EPS figures may deviate systematically from the I/B/E/S figures. I have no predictions for the direction or magnitude of specific coefficients in this analysis; the aim is to explore whether certain brokers deviate in a particular direction.

Insert Table 2.5 about here

Table 2.5, Panel A reports the results of regressions of analyst-I/B/E/S differences in non-GAAP actual EPS on brokerage firm fixed effects. In column 1, I report the results with the analyst- I/B/E/S difference in non-GAAP actual EPS scaled by stock price, while column (2) shows estimates deflated by absolute I/B/E/S non-GAAP actual EPS. I find significant deviations of many brokerage firms from the baseline brokerage firm (Barclays), implying that brokerage firms have different methods of adjusting non-GAAP EPS.

Panel B of Table 2.5 reports the estimation results of regressing analyst-I/B/E/S difference in GAAP actual EPS on brokerage firm fixed effects. Although some brokerage firm fixed effects are different from zero, the number of coefficients statistically different from zero in Panel A is more than twice as high as the number in the Panel B (14 compared to 6 for the case of *DIFFACT_P*).

These findings again show that there is significantly more disagreement between analysts regarding non-GAAP actual EPS compared to GAAP figures, illustrating how the GAAP reporting regime allows less discretion for analysts in choosing the relevant earnings measures for valuation purposes. Even though GAAP EPS figures may be less useful for forecasting because they include more transitory items (Bentley et al., 2018; Black et al., 2018; Gu and Chen, 2004; Young, 2014), the GAAP reporting regime seems better suited to fulfilling the confirmatory role of accounting information due to its consistency across preparers and across analysts. In the case of GAAP reports, there is a lower risk that the measurement basis of actual earnings will be ambiguous ex post, making it more suitable for forecast evaluation.

2.4.5 Broker size effect

Next, I explore whether broker size, a proxy for the resources analysts have access to (Clement, 1999; Bilinski et al., 2013), can explain part of the analyst-I/B/E/S difference in non-GAAP actual EPS. Clement (1999) argues that analysts employed by large brokerage firms may have better access to research facilities, administrative support, and managers' private information. It is therefore possible that analysts with access to a larger pool of resources and expertise in accounting adjustments may choose to deviate from the majority in order to signal their private information.

Insert Table 2.6 about here

Table 2.6 Panel A reports the results of tests for variation in the level of analyst-I/B/E/S differences in non-GAAP actual EPS across top brokers and non-top brokers. An analyst is deemed a top broker analyst if his/her employer is classified as such by the Financial Times. Using the analyst-I/B/E/S difference in non-GAAP actual EPS scaled by stock price (*DIFFACT_P*), I find that the mean of *DIFFACT_P* is positive in the top broker sample but negative in the smaller broker sample, and the difference is statistically significant at the 1 percent level. I find similar results when the analyst-I/B/E/S difference in non-GAAP actual EPS is scaled by absolute I/B/E/S non-GAAP actual EPS (*DIFFACT_IBES*). These findings suggest that, on average, analysts working for top brokers tend to exclude more income decreasing items, leading to non-GAAP actual EPS being higher than I/B/E/S actual EPS. This further confirms the findings regarding the lack of consistency across brokerage firms in non-GAAP EPS adjustments I find above. However, I do not find that large brokers make more adjustments.

Panel B of Table 2.6 reports the test results for the analyst-I/B/E/S difference in GAAP actual EPS across top and non-top brokers. Interestingly, using the measure scaled by stock prices, I find that the level of analyst-I/B/E/S differences in GAAP actual EPS in the top broker sample is very similar to that in the non-top broker sample. When the differences is deflated by the absolute I/B/E/S GAAP actual EPS, there are some differences between top brokers and smaller brokers, nevertheless, these differences are statistically insignificant. There are, however, large outliers in the GAAP distribution. These findings suggest that the GAAP reporting regime limits analysts' opportunities to make discretionary adjustments, regardless of whether the adjustments are for signalling skills or to cater to opportunistic incentives.

Returning to my research questions, the findings point to non-GAAP actual EPS measures differing significantly across analysts and compared with I/B/E/S actuals; however, this variation is far less problematic for GAAP EPS, where the degree of consistency across analysts is much higher.

2.4.6 Evaluating Forecast Properties using Non-GAAP and GAAP EPS

Most prior studies evaluating the properties of analysts' forecasts rely on I/B/E/S measures for both forecasts and actual earnings (e.g. DeBondt and Thaler, 1990; Keane and Runkle, 1998; Capstaff et al., 2001; Bradshaw and Sloan, 2002; Basu and Markov, 2004; Abarbanell and Lehavy, 2007). An important implication of my findings that analysts' own EPS often differ substantially from I/B/E/S actuals is that I/B/E/S data may not represent the measure of earnings used by analysts when they formed their forecasts. To address the RQ 3, I examine analysts' own actual and forecast data to align the measure of earnings analysts were using when they issued their forecasts. This analysis requires collection of EPS forecasts from analysts' reports at time *t* and actual earnings in a subsequent report by the same analyst at time *t*+1.

Table 2.7 reports the results for forecast accuracy (Panel A) and bias (Panel B) for non-GAAP EPS forecasts. To prevent the results from being unduly influenced by outliers, I eliminate observations where the forecast error is more than 400%, 300%, 200% and 100% of the denominator of forecast error variables. This is because prior research on the properties of European analysts' forecasts indicates that forecast properties are sensitive to different outlier treatments (Capstaff, et al., 2001). I report the full sample results, together with results where the sample is trimmed to eliminate outliers at different points in the distribution.[6]

Insert Table 2.7 about here

Panel A of Table 2.7 shows the forecast error for non-GAAP EPS calculated from analysts' report data using two different measures of forecast error. This reflects the fact that in some instances, there are different measures of actual GAAP EPS for the same analyst for the same bank year. Analyst_*minnonGAAPFE* is based on the minimum forecast error for the different actual EPS measures, while *Analyst_nonGAAPFE* is based on the actual

[6] The number of observations is lower in this analysis because I require both a forecast and an actual value by the same analyst for the same bank-year and these are not always available in Investext.

EPS figure immediately after the earnings announcement date (i.e., the earliest available actual EPS figures). For comparison with the sample, I also report forecast errors based on I/B/E/S actual and forecast data (*IBESnonGAAPFE*). All data in Panel A are deflated by the absolute value of I/B/E/S actual EPS.

In the full sample, I find that the mean forecast error based on analysts' own actual EPS is larger than that obtained from I/B/E/S. However, there are large outliers in analysts' data, particularly a maximum absolute forecast error for both *Analyst_minnonGAAPFE* and *Analyst_nonGAAPFE* of 36.667.[7] Since the patterns in the trimmed samples are generally similar, I focus the discussion on the 100% trimmed sample.

Both *Analyst_minnonGAAPFE* and *Analyst_nonGAAPFE* have lower means than *IBESnonGAAPFE* (0.172 and 0.193 compared to 0.263). The medians and standard deviations of *Analyst_minnonGAAPFE* and *Analyst_nonGAAPFE* are also larger for *IBESnonGAAPFE* (the medians are 1.5 to 1.8 times higher for I/B/E/S). Moreover, the differences are not attributable to outliers in either sample. These findings indicate that, when matched to analysts' own actual EPS, the forecasts obtained from analysts' reports are more accurate than those from I/B/E/S. In other words, based on the sample of European banks, using I/B/E/S data may lead to an underestimation of the precision of analysts' non-GAAP forecasts.

Panel B of Table 2.7 presents the forecast bias of non-GAAP EPS, which is the signed version of the forecast error in Panel A. Consistent with a wealth of prior literature, the results for the full sample show that analysts' earnings forecasts are optimistically biased: all means and medians are negative, i.e. actual non-GAAP EPS is lower than analyst non-GAAP forecasts. The mean and median bias obtained from analysts' reports

[7] Further investigation showed that this observation is affected by a small denominator, rather than a particularly large numerator.

(*Analyst_nonGAAPbias_min* and *Analyst_nonGAAPbias*) are significantly lower than I/B/E/S data (*IBESnonGAAPbias*) in the full sample. Nevertheless, similar to the case of forecast accuracy above, these statistics are affected by outliers: the minimum *Analyst_nonGAAPbias_min* and *Analyst_nonGAAPbias* is -36.667, over 8 times the minimum value of *IBESnonGAAPbias* (-4.204).

Eliminating a small number of outliers reduces the bias of non-GAAP analyst forecasts calculated from analysts' own data significantly. The mean of *Analyst_nonGAAPbias_min* changes dramatically, from -0.422 in the full sample to -0.057 in the 100% trimming sample. I find a similar pattern for *Analyst_nonGAAPbias.* After eliminating the outliers, I still find that analyst optimism bias in non-GAAP EPS calculated from analysts' own data remains higher than when it is based on I/B/E/S data. This finding is not affected by the treatment of outliers or by the use of share price as a deflator.

Insert Table 2.8 about here

Table 2.8, Panel A presents the GAAP EPS forecast accuracy measures calculated from analyst reports (*Analyst_minGAAPFE* and *Analyst_GAAPFE*) and I/B/E/S data (*IBES_GAAPFE*). I further compare GAAP forecasts from analyst reports and I/B/E/S forecasts with the actual GAAP EPS reported in banks' annual reports (*GAAPFE_AnaCom* and *GAAPFE_IBESCom*). There are notable differences between the means of these variables in the full sample. Specifically, the means and standard deviations of *IBES_GAAPFE* and *GAAPFE_IBESCom* are significantly higher than the comparable figures calculated from analysts' reports. However, the differences are influenced by the very large outliers of *IBES_GAAPFE* and *GAAPFE_IBESCom* (1080.70), which shows that the difference between forecast and actual EPS can be over one thousand times larger than the denominator.[8] When the outliers are eliminated, the distributions of these variables in the 100% trimming sample are very similar. However, the means and medians of *IBES_GAAPFE* and *GAAPFE_IBESCom* are marginally higher than the variables based on analysts' own EPS figures.

I find similar patterns in Panel B of Table 2.8, which shows the GAAP EPS forecast bias obtained from analyst report data and I/B/E/S data (*Analyst_GAAPbias_min*, *Analyst_GAAPbias* and *IBES_GAAPbias* respectively). I also calculate the bias of forecasts compared to GAAP EPS reported from company annual reports (*GAAPbias_AnaCom* and *GAAPbias_IBESCom*). Although forecasts based on I/B/E/S data are more optimistically biased in the full sample, the findings are again influenced by very negative outliers. When I remove these, the differences narrow, so that the distributions of all GAAP measures look very similar.

Overall, the findings in Tables 7 and 8 indicate that non-GAAP forecast accuracy and bias measures calculated with analysts' own actual EPS measures differ significantly from those obtained from the I/B/E/S dataset. These differences may affect the conclusions of studies using non-GAAP earnings forecasts from I/B/E/S to assess forecast accuracy. Specifically, the level of bank analyst forecast accuracy is higher than the I/B/E/S data indicates, although the level of bias is also higher based on analysts' own actual earnings per share.

In contrast to the findings for non-GAAP forecasts, however, the descriptive statistics on GAAP forecast accuracy and bias show no evidence of significant differences between measures calculated from the hand collected data and those obtained from I/B/E/S – and with those reported by the respective bank itself.

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[8] Such extreme negative values in analysts' forecast errors using data from several commercial data providers are also documented by Abarbanell and Lehavy (2003), who refer to a significant 'tail asymmetry' in the forecast error distribution.

2.4.7 Analyst forecast rationality tests: Non-GAAP and GAAP EPS

After examining the univariate statistics on analyst forecast accuracy and biases, I then study whether analysts rationally forecast non-GAAP and GAAP earnings in a bivariate regression analysis. In the first tests, actual EPS (denoted *A*) is regressed on forecast EPS (denoted *F*) using data obtained from both analyst reports and from I/B/E/S (e.g. Holden and Peel, 1990; Keane and Runkle, 1990; 1998).

$$A_t = \alpha_0 + \alpha_1 F_{t,t-h} + \varepsilon_t \qquad (2.1)$$

If forecasts are rational, and assuming analysts have a quadratic loss function,[9] I expect $\alpha_0 = 0$ and $\alpha_1 = 1$ (i.e., $E\left(e_t\right) = 0$). Table 2.9 reports the results of these tests, where both A_t and $F_{t,t-h}$ are deflated by the most recent stock price at the time of the forecast. Panel A reports the results for non-GAAP forecasts, while Panel B reports the estimates for GAAP forecasts. I follow Capstaff, Paudyal and Rees (2001) by reporting results for both the full sample and trimmed samples.

Insert Table 2.9 about here

The estimates of α_0 using analysts' own actual earnings figures are negative in the full sample, but only weakly different from zero in both the full sample and the trimmed samples. In contrast, the estimates for α_0 based on I/B/E/S data are significant and positive in all non-GAAP EPS regressions. The coefficient for α_1 is significantly below one in Panel A, Table 2.9, using both analysts' own actual EPS and the I/B/E/S sample. Importantly, however, the estimates of α_1 based on I/B/E/S data depart substantially from their hypothesised value of one, the closest being 0.531 where the distribution is trimmed at 100% of share price. Based on analysts' own data, the estimates of α_1 are around 0.90 regardless of outlier treatment. Overall, I reject the hypothesis that analysts' forecasts of non-GAAP

[9] Prior research suggests this assumption should be made with caution (Basu and Markov, 2004; Clatworthy, Peel and Pope, 2012).

EPS are rational using both sets of data. However, forecasts appear to be much closer to their hypothesized values when using analysts' own EPS measures compared with those supplied by I/B/E/S.

Panel B of Table 2.9 reports the estimates for model (2.1) for GAAP EPS forecasts. I reject the hypothesis that analysts' GAAP EPS forecasts are rational using both sets of data: α_0 is significantly different from zero and α_1 is significantly different from one. However, with the exception of the full sample, where α_1 is 0.446, the results for the two samples are very similar and α_1 is much closer to 1 in all other regressions. This again shows that both I/B/E/S and analysts' own data yield economically similar results regarding analyst unbiasedness in forecasting GAAP EPS. The estimates are also much closer to their hypothesised values for both data sets.

2.4.8 Analyst over-reaction tests

I complement the tests in Table 2.9 with tests of over or under reaction (De Bondt and Thaler, 1990; Capstaff, Paudyal and Rees, 2001), by regressing the actual change in earnings on the forecast change for both GAAP and non-GAAP forecasts:

$$\frac{\left(A_t - A_{t-1}\right)}{\left|A_{t-1}\right|} = \gamma_0 + \gamma_1 \frac{\left(F_{t,t-h} - A_{t-1}\right)}{\left|A_{t-1}\right|} + \eta_t \tag{2.2}$$

Again, the null hypotheses are that g_0 = 0 and g_1 = 1. Capstaff, Paudyal and Rees (2001) interpret a positive g_0 as evidence of pessimistic bias, while a negative g_0 implies an optimistic bias. De Bondt and Thaler (1990) and Capstaff, Paudyal and Rees (2001) suggest that analysts overreact (underreact) when g_1 is smaller (larger) than 1 because the actual change in EPS is higher (lower) than the forecast change.

Insert Table 2.10 about here

Table 2.10, Panel A reports the estimates for equation (2.2) using non-GAAP forecasts and analysts' own actual EPS compared with I/B/E/S. Consistent with prior research, the coefficient g_1 is significantly lower than one in Panel A, implying that analysts overreact to earnings information when forecasting non-GAAP earnings. However, for all regressions except where I trim at 100% of stock price, the extent of over-reaction is lower (and significant in two out of three cases) when using analysts' own earnings measures.

The estimates of g_0 in Panel A of Table 2.10 mainly differ from zero only for the I/B/E/S sample, suggesting that analysts are pessimistically biased when forecasting non-GAAP EPS changes. This stands in contrast to prior research on (non-financial) European samples using I/B/E/S data, which reports a negative intercept (Capstaff et al., 2001). The evidence from Table 2.10, Panel B also leads to us rejecting the hypothesis that analysts can forecast GAAP EPS changes rationally: g_0 is generally significantly different from zero, and is negative for stricter outlier treatments. When outliers are trimmed at (at least) twice the level of share price, forecast changes are closest to (and sometimes statistically indistinguishable from) actual earnings changes. This suggests that the level of analyst overreaction is less pronounced for GAAP EPS forecasts.

Overall, the findings from Tables 9 and 10 lead to us rejecting the argument that analysts can rationally forecast levels of and changes in GAAP and non-GAAP EPS. However, the estimated coefficients are typically closer to their hypothesized values when analysts' own actual EPS data are used. Moreover, as shown in prior research, estimates are sensitive to the outlier trimming rules employed.

2.4.9 The relation between analyst non-GAAP adjustments and future forecast errors

In this section, using I/B/E/S non-GAAP actual EPS as a benchmark, I explore whether individual analysts' adjustments to non-GAAP EPS measures are reflected in their forecast accuracy. The level of analyst-I/B/E/S differences in past actual non-GAAP EPS may reflect two possible sets of information. First, it may reflect useful information conveyed by skilful analysts with private information about banks they cover who choose to exclude certain expenses which they consider transitory from past earnings. Second, analyst-I/B/E/S differences may reflect analysts' strategic biases. As Gu and Chen (2004) note, when given full discretion over their measurement of earnings, analysts may strategically choose an actual earnings figure that closely matches their previous forecast. Some analysts may thus opportunistically exclude some items which are not necessarily transitory, from both non-GAAP EPS forecasts and actuals. In both ways, some analysts' actual non-GAAP EPS may deviate significantly from the actual non-GAAP EPS based on the majority rule of I/B/E/S.

If all analysts can see through these signals, they will discount the information appropriately into their current forecasts and thus there should be no relation between the analyst-I/B/E/S differences about past non-GAAP actual EPS and their future forecast errors. However, if some analysts fail to see through this information, there should be a relation between current analyst-I/B/E/S differences about past non-GAAP actual EPS and future forecast errors.

Similar in spirit to Bradshaw, Richardson and Sloan (2001), who test whether analysts use information from accruals appropriately by regressing future forecast errors on accruals rank, I regress future non-GAAP EPS forecast errors on the current analyst-I/B/E/S differences in past non-GAAP actual EPS:

$$\left|\frac{A^{Ana}_{i,j,t} - F_{i,j,t,t-1}}{P_{t-1}}\right| = \delta_0 + \delta_1 \frac{A^{Ana}_{i,j,t-1} - A^{IBES}_{i,t-1}}{P_{t-1}} + e_t \tag{2.3}$$

Table 2.11, Panel A reports the results of this test. Column (1) shows the OLS estimation of Eq. (2.3) without including fixed effects, column (2) controls for broker fixed effects, while column (3) includes both broker and bank fixed effects. The constant term in column (1) reflects the average forecast error for the case of zero analyst-I/B/E/S differences regarding past non-GAAP actual EPS. The main interest lies in the coefficient for *PREACT_DIFF,* which is significantly negative. This implies that when analysts' actual EPS at time *t* is higher than the consensus, their subsequent forecasts are more accurate. However, I am unable to determine whether the information contained in analyst-I/B/E/S differences about past non-GAAP actual EPS reflects analysts' skill or optimistic bias.

Insert Table 2.11 about here

To substantiate the test above, I expect that the relation between analyst-I/B/E/S differences about past actual EPS only exists in the non-GAAP reporting regime, where analysts have discretion over adjustments they can make to the non-GAAP actuals. With the GAAP regime, analysts are disciplined by auditors and by adherence to agreed accounting standards. They are therefore unable to convey the skills or opportunistic biases via the analyst-I/B/E/S differences. Table 2.11, Panel B shows that the coefficient on the analyst-I/B/E/S differences about past GAAP actual EPS (*PREACT_DIFF)* is insignificantly different from zero.

Overall, the findings of the Table 2.11 suggest that analyst-I/B/E/S differences about past non-GAAP actual EPS contain useful information about either analysts' skills or opportunistic biases and this information has not been appropriately incorporated into future forecasts.

While it is difficult to evaluate whether the analyst-I/B/E/S differences about past non-GAAP actual EPS contain information about biases or not, it is possible to test whether the construct contains information about analyst skills. If some analysts possess superior skills in forecasting future earnings, and they signal the skills via their adjustments in non-GAAP EPS, then they should perform better in forecasting future GAAP EPS. As I show in previous tests, the GAAP reporting regime tends to discipline analysts and prevent them from strategically reporting their GAAP actual earnings figures. Furthermore, analysts' strategic biases related to excluding items from GAAP figures are unlikely to be related to GAAP forecasts. Therefore, analysts with superior forecasting skill are likely to produce more accurate GAAP forecasts and choose to convey information about their skills through larger adjustment in the non-GAAP forecast and actual EPS. This reasoning points to analysts with larger analyst-I/B/E/S non-GAAP differences being associated with higher GAAP forecast accuracy.

To test this prediction, I regress future GAAP forecast error on analyst-I/B/E/S differences about past non-GAAP actual EPS. According to the predictions, I expect the relationship between future GAAP forecast errors and analyst-I/B/E/S non-GAAP differences to be negative. Table 2.12 presents the results of this analysis. Consistent with the prediction, when I do not control for bank and broker fixed effects, the coefficient of *PREACT_DIFF_NonGAAP* is negative and significant at the 10 percent level. When I control for broker or bank fixed effects, the coefficient is still negative but not statistically significant. Overall, the findings of this test provide weak support for the argument that analyst-I/B/E/S differences about past non-GAAP actual EPS reflect analyst ability.

2.4.10 The persistence of analyst-I/B/E/S differences in past actual non-GAAP EPS

In this section, I examine the persistence of analyst-I/B/E/S differences in past actual non-GAAP EPS. Laurion (2020) suggests that non-GAAP-reporting firms tend to repeat their restructuring activities and related accounting choices year-after-year, resulting in more persistent special-item expenses which are typically excluded from their non-GAAP earnings. If analysts tend to consistently exclude these special-item expenses, I expect that the analyst-I/B/E/S differences in past actual non-GAAP EPS to be persistent across years. To test this expectation, I regress analyst-I/B/E/S differences in actual non-GAAP EPS on the past differences:

$$\frac{\left(A_{i,j,t}^{Ana}-A_{i,t}^{IBES}\right)}{P_t}=\lambda_0+\lambda_1\frac{\left(A_{i,j,t-1}^{Ana}-A_{i,t-1}^{IBES}\right)}{P_{t-1}}+\mu_t \qquad (4)$$

Table 2.13, Panel A presents the results for these tests. Column (1) shows the OLS estimation of Eq. (2.5) without controlling for any fixed effects, column (2) controls for broker fixed effects, while column (3) includes both broker and year fixed effects. The coefficient I am interested in is *DIFFACT_P$_{t-1}$*, which is positive and significant in all columns. This reflects my expectation about the persistence of analyst-I/B/E/S differences in past actual non-GAAP EPS and implies that analysts consistently exclude at least part of certain special-item expenses throughout the years. This finding does not indicate whether analysts' decisions to exclude those items are driven by their skills or opportunistic biases. Nevertheless, if the special items tend to be persistent through time, these items are actually recurring by nature and questions the notion that these items are excluded because they are transitory (Black et al., 2018). Furthermore, the persistence of analyst-I/B/E/S differences in past actual non-GAAP EPS also implies that the persistence of these special items drives the persistent disagreement between analysts regarding whether companies should exclude these items from their core earnings. In other words, when companies disclose their non-GAAP earnings, the additional disclosure does not necessarily resolve uncertainty regarding future performance because analysts and market participants may still disagree about whether certain recurring special items should be excluded.

To complement these tests above, I examine the GAAP earnings forecasts sample. I expect that the persistence in analyst-I/B/E/S differences about past actual earnings only exists in the non-GAAP reporting regime due to the disciplining roles of auditors and GAAP standards. Since analysts are unable to convey the skills or opportunistic biases via the analyst-I/B/E/S differences about past GAAP actual EPS in the GAAP reporting regime, I expect there to be no persistence in analyst-I/B/E/S differences about past actual EPS. Table

2.13, Panel B shows that the coefficient of the main variable of interest, $DIFFACT\_P_{t-1}$, is significant when no fixed effects are included, but becomes insignificant when control for fixed effects.

Overall, the findings of Table 2.13 suggest that analyst-I/B/E/S differences about past non-GAAP actual EPS are persistent and are likely be driven by analysts consistently excluding special-item expenses – at least in part. However, this persistence test, similar to the previous test, cannot distinguish whether analysts' decision to consistently exclude certain items from GAAP earnings signal their skills or behavioural biases.

2.5 Conclusions

One of the main roles of accounting information is to confirm prior expectations and to discipline and evaluate forecasts made by firms and information intermediaries. Knowledge of the properties of equity analysts' forecasts is valuable to assess their usefulness in fundamental investment strategies and in the estimation of cost of equity. Prior conclusions in the literature on the levels of accuracy and bias inherent in analysts' earnings forecasts are based on actual and forecast data from commercial data providers such as I/B/E/S, which report a single actual earnings figure for each firm year.

Based on a sample of large European banks, which are economically important, complex and opaque institutions, this study shows that there is significant disagreement about what companies' non-GAAP earnings were, as well as what they are expected to be. It is therefore difficult to condense the various earnings measurement bases used by analysts into one single 'street' earnings figure. Importantly, the results also show that the GAAP system does not permit analysts such discretion.

My results indicate that analysts' forecasts appear more accurate and more biased when using analysts' own measurement bases, compared to when I/B/E/S actuals are used.

However, I am unable to ascertain whether analysts are using their preferred measure of actual EPS strategically ex post to justify earlier forecasts of a particular magnitude. My results are partly contingent on the treatment of outliers and there seem to be no systematic patterns across banks or brokers. These findings contribute to the literature on non-GAAP reporting by revealing that not only are there differences between analysts and managers over the definition of non-GAAP earnings (Bentley et al., 2018), there are also significant differences across analysts. This creates uncertainty about the extent to which forecasts have been met ex post and thus potentially undermines the disciplining role of accounting. However, the consistency across analysts (and managers) with respect to GAAP earnings definitions indicates that although they are more likely to contain transitory items (Young, 2014; Black et al., 2018), GAAP earnings are less vulnerable to the measurement ambiguity across analysts.

Although they are large and important institutions, the focus on the earnings of banks comes at the expense of generalizability to other sectors. Further research will be necessary to determine the extent of disagreement between analysts about the prior earnings of less complex companies. In addition, the sample of this study consists of both European banks and UK banks. Future research could further analyse the difference between UK and European banks given the difference in institutional environment. Estimation procedures that take account of correlated errors across analysts will also enhance the reliability of inferences (Keane and Runkle, 1990; 1998).

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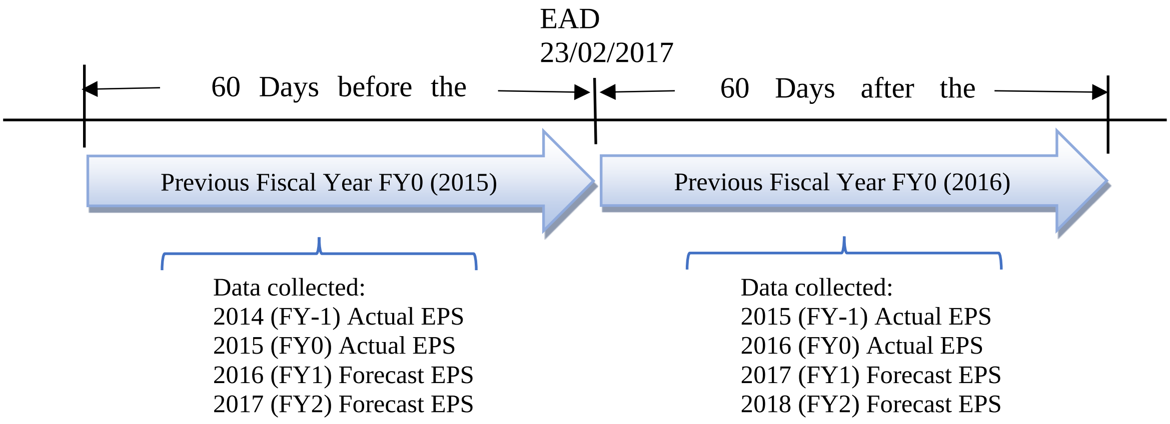
Figures of Chapter 2

Figure 2.1 Example of data collection timeline for Barclays 2017



This figure presents the timeline to illustrate the data collection procedure using Barclays' earnings announcement date of 23/02/2017 as an example. I obtain analysts' reports issued 60 days before and 60 days after the earnings announcement date for each bank. I record information on the current fiscal year (FY1), the earnings announcement date, broker name, analyst(s) name(s), stock price, price target, recommendation, analyst report date, previous fiscal year (FY0), description of GAAP EPS and non-GAAP EPS, actual EPS reported for the previous fiscal year (FY0) and the year before previous fiscal year (FY-1), as well as forecast EPS reported for the current fiscal year (FY1) and for the next fiscal year (FY2).

Tables of Chapter 2

Table 2.1 Reconciliations of GAAP and non-GAAP EPS in analysts' reports

This table reports the GAAP and non-GAAP reconciliations in analysts' reports. Column (1) shows the results for pooled sample. Columns 2 and 3 show the results for the samples with and without detailed GAAP and non-GAAP reconciliations in banks' annual reports, respectively. The pooled sample consists of 4 large UK banks and 5 European banks between 2010 and 2013. The sample without reconciliations in banks' annual reports comprises Credit Agricole and BNP Paribas. The sample with detailed reconciliation in annual reports consist of the remaining 4 large UK banks and 3 European banks between 2010 and 2013. Analysts' reports are coded as '*No reconciliation*' if no information on GAAP and non-GAAP reconciliations can be found in the reports. Analysts' reports are coded as '*Limited reconciliation*' if a partial reconciliation between GAAP and non-GAAP are disclosed in analysts' reports. Analysts' reports are coded as '*Detailed reconciliation*' if comprehensive information on GAAP and non-GAAP reconciliations are disclosed in the reports.

	(1) Pooled sample		(2) Sample with detailed reconciliation in annual reports		(3) Sample without reconciliation in annual reports	
	Number of analysts' reports	Percentage	Number of analysts' reports	Percentage	Number of analysts' reports	Percentage
No Reconciliation	242	48.02%	199	46.71%	43	55.13%
Limited Reconciliation	157	31.15%	132	30.99%	25	32.05%
Detailed Reconciliation	105	20.83%	95	22.30%	10	12.82%
Total	504	100.00%	426	100.00%	78	100.00%

Table 2.2 Illustrative example – HSBC

This table provides the illustrative example for the case of GAAP and non-GAAP actual EPS variations. Panel A provides the variations of GAAP and non-GAAP actual EPS across analyst reports while panel B reports the detailed reconciliation information.

Panel A. GAAP and Non-GAAP EPS variations

Broker	Report date	GAAP EPS	Non-GAAP EPS
UBS	4-Mar-13	0.74	0.76
Deutsche Bank	5-Mar-13	0.75	1.94
Morgan Stanley	5-Mar-13	0.75	0.9
RBC Capital	4-Mar-13		
Societe Generale	5-Mar-13	0.75	0.9
RBC Capital	5-Mar-13		0.89
Edison	15-Mar-13	0.74	
Credit Suisse	25-Mar-13	0.73	1.06
Macquarie	26-Mar-13	0.74	0.8
Liberum	12-Apr-13	0.736	0.854
Deutsche Bank	1-May-13	0.75	0.93

Table 2.2 (continued)

Panel B. Detailed reconciliation between GAAP and non-GAAP

		Non-GAAP Measures																**GAAP Measures**	
		Adj. Net income (after-tax)	**Clean PBT**	Own credit spread	Acquisition, disposals & dilutions	UK customer redress programs	US Fines & penalties	UK Pension credit	Restructure & other related costs	Goodwill	Extraordinary & other items	Non-qualifying hedges	US Mortgage foreclosure and serving costs	Ping An contingent forward sale	Gain on sales of non-core investment in India	Bank levy	Loss recognised on reclassification to held for sale	**Pre-tax profits**	**Net profit (after-tax)**
UBS	4-Mar-13			-5215	9048	-2300	-1900	0	-900									20649	13454
Deutsche Bank	5-Mar-13	35473								-969	-20911							21618	13593
Morgan Stanley	5-Mar-13		24710	-5220	6690	-5240												20650	14030
RBC Capital	4-Mar-13		24271	-5215	7024	-4259			-876			-300	-104					20649	14027
Societe Generale	5-Mar-13	16404	24213	-5215	7024	-4200			-876			-296						20650	13454
RBC Capital	5-Mar-13		23446	-5215	7849	-4259			-876			-296						20649	13454
Edison	15-Mar-13		22623	-5215	9479	-2338			-876			-296		-553	314	-472	-96	20649	14027
Credit Suisse	25-Mar-13	16679	23199	-5215	9479	-2338	-1921		-876		-335	-296				-472		21121	13454
Macquarie	26-Mar-13	14647	22255								-1606	-296						20649	14027
Liberum	12-Apr-13																	20649	13454
Deutsche Bank	1-May-13	16929								-969	-2367								13593

Table 2.3 Descriptive statistics of the difference between analysts' actual EPS and I/B/E/S actual EPS

This table reports the summary statistics of the differences between the Non-GAAP actual EPS obtained from analysts' reports and those from I/B/E/S across the nine banks in the sample (*DIFFACT_P*). I scale the differences between analysts' EPS and I/B/E/S EPS by the stock price reported in analysts' reports.

Variable	N	Mean	Median	Std	P1	P99
Non-GAAP						
DIFFACT_P	2019	0.0458	0.0170	0.0992	0.0000	0.4650
GAAP						
DIFFACT_P	1840	0.0136	0.0016	0.0531	0.0000	0.1670

Table 2.4 Regression Results: Bank Fixed Effects

This table reports the regression results of differences between analysts' actual EPS and I/B/E/S actual EPS on bank fixed effects. Column (1) shows the results using stock price as a deflator, while column (2) shows results deflated by the absolute value of I/B/E/S actual EPS. Panel A presents the regression results for non-GAAP actual EPS differences. Panel B presents the regression results of GAAP actual EPS differences. All variable definitions are presented in Appendix A2.1. Robust t-statistics are reported in parentheses. *, **, *** indicate significance levels (two-sided) at 10%, 5% and 1%, respectively.

Panel A Non-GAAP EPS actual difference between analysts and I/B/E/S (bank fixed effect)

Variables	(1) *DIFFACT_P*	(2) *DIFFACT_IBES*
BNP Paribas	-0.0150***	-0.1870***
	(-5.15)	(-6.29)
Credit Agricole	-0.0449***	-0.2850***
	(-5.68)	(-4.87)
Deutsche Bank	-0.0452***	-0.3330***
	(-5.70)	(-5.92)
HSBC	-0.0045*	-0.0263
	(-1.80)	(-0.83)
ING	-0.0181***	-0.2590***
	(-5.78)	(-6.07)
KBC	0.1080***	0.8030***
	(5.70)	(11.25)
Lloyds	-0.0365***	-0.4920***
	(-6.53)	(-11.56)
RBS	-0.0668***	-0.5500***
	(-10.39)	(-10.57)
Barclays	0.0093***	0.1350***
	(4.07)	(5.30)
Observations	2,019	2,021
R-squared	0.158	0.257

Table 2.4 (continued)

Panel B GAAP EPS actual difference between analysts and I/B/E/S (bank fixed effect)

Variables	(1) *DIFFACT_P*	(2) *DIFFACT_IBES*
BNP Paribas	0.0028	1.0250
	(1.09)	(1.46)
Credit Agricole	0.0019	-0.1010
	(0.80)	(-1.13)
Deutsche Bank	0.0054**	0.0942
	(1.98)	(0.98)
HSBC	0.0006	-0.0391
	(0.27)	(-0.41)
ING	0.0009	-0.0671
	(0.33)	(-0.74)
KBC	0.0305***	-5.8050**
	(4.35)	(-2.56)
Lloyds	-0.007	-0.1160
	(-1.19)	(-1.15)
RBS	0.0128*	-0.1800*
	(1.87)	(-1.84)
Barclays	0.0005	0.1240
	(0.21)	(1.40)
Observations	1,840	1,842
R-squared	0.032	0.033

Table 2.5 Regression Results: Broker Fixed Effects

This table reports the regression results of differences between analysts' own actual EPS and I/B/E/S actual EPS on broker fixed effects. Column (1) shows results using stock price deflation, while column (2) shows results using the absolute value of I/B/E/S actual EPS as a denominator. Panel A presents the regression results of non-GAAP actual EPS difference between analysts and IBES. Panel B presents the results for GAAP actual EPS. All variable definitions are presented in Appendix A2.1. *, **, *** indicate significance levels (two-sided) of 10%, 5% and 1%, respectively.

Panel A Non-GAAP EPS actual difference between analysts and I/B/E/S (broker fixed effects)

Variables	*DIFFACT_P* *(1)*	*DIFFACT_IBES* (2)
ABN AMRO	0.0115	0.0798
BNP Paribas	0.0116	0.0769
Berenberg	-0.0518***	-0.2650**
Canaccord	-0.0508	-0.5710
Cheuvreux	0.0526***	0.5540**
Collins Stewart	0.0199**	0.2000**
Commerzbank	-0.0744	-0.3390
Credit Suisse	-0.0071	-0.0790
Davy Research	-0.0839***	-0.7570***
Deutsche Bank	0.0253**	0.2520***
EQUITA	0.0140	0.1110*
ESN	-0.0563***	-0.3560**
Evolution	-0.0012	-0.0968
HSBC	0.0084	0.3140**
ING	0.2060***	0.8730***
Investec	-0.0256	-0.2990*
JP Morgan	0.0031	0.0129
Jefferies	0.0081	0.0504
KBC	-0.0053	-0.2850
Kepler	0.0041	0.0712
Liberum	0.0242***	0.2570***
Macquarie	0.0295**	0.2680***
MainFirst	0.0098	0.0797
Mediobanca	0.1310***	0.9790***
Morgan Stanley	0.0331***	0.2110***
Natixis	-0.0569**	-0.3800***
Numis	0.0154	0.0982
Petercam	0.0135	0.1030*
RBC	-0.0093	-0.0928
RBS	0.0200	0.368**
Santander	0.0207*	0.1450
Societe Generale	-0.0064	0.0455
UBS	0.0050	0.0722
Warburg	0.0299***	0.2900***
Barclays	-0.0135	-0.1030*
Observations	2,019	2,019
R-squared	0.090	0.097

Table 2.5 (continued)

Panel B GAAP EPS actual difference between analysts and I/B/E/S (broker fixed effects)

Variables	*DIFFACT_P* (3)	*DIFFACT_IBES* (4)
ABN AMRO	0.0096*	0.1530*
BNP Paribas	-0.0025	0.1130
Berenberg	-0.0032	-3.1510
Canaccord	0.0084	0.2320
Cheuvreux	0.0108**	0.0664
Collins Stewart	0.0077	0.0176
Credit Suisse	-0.0007	-0.0282
DBS	-0.0035	-0.0548
Deutsche Bank	0.0035	-2.5680**
EQUITA	-0.0019	-0.0372
ESN	0.0063	0.1980**
HSBC	0.0049	0.1730
ING	0.0273***	0.5930***
Investec	-0.0019	-0.0565
JP Morgan	-0.0006	-0.0034
Jefferies	-0.0033	-0.0871
KBC	-0.0024	-0.0366
Kepler	0.0091**	0.2450***
Liberum	-0.0042	-0.0631
Macquarie	0.0018	-1.7100
MainFirst	0.0002	0.6540**
Mediobanca	0.0202**	0.2330*
Morgan Stanley	-0.0003	1.1140
Natixis	-0.0031	-0.0357
Numis	-0.0029	-0.0099
Petercam	-0.0041	-0.0590
RBC	-0.0056	-0.0746
RBS	0.0059	0.0075
Santander	0.0104	0.1160
Societe Generale	0.0047	1.3700
UBS	-0.0027	-0.4290
Warburg	0.0131***	0.1380***
Barclays	0.0038	0.0577
Observations	1,840	1,842
R-squared	0.008	0.017

Table 2.6 Descriptive statistics for actual EPS difference between analysts and I/B/E/S: Broker Size Effect

This table reports broker effects on actual EPS differences between analysts and I/B/E/S. The actual EPS difference between analysts and IBES is scaled by stock price taken from analysts' reports or the absolute value of I/B/E/S actual EPS. Panel A reports results for non-GAAP data. Panel B reports results for GAAP data. All variable definitions are presented in Appendix A2.1. *, **, *** indicate significance levels (two-sided) of 10%, 5% and 1%, respectively.

Panel A Non-GAAP EPS actual difference between analysts and I/B/E/S (by broker characteristics)

	DIFFACT_P			*Mean difference test*	*DIFFACT_IBES*			*Mean difference test*
	Top Broker				*Top Broker*			
	Yes	No	Total		Yes	No	Total	
N	791	1228	2019		791	1230	2021	
Mean	0.002	-0.013	-0.007	-0.0148***	0.019	-0.066	-0.033	-0.0845***
S.d.	0.112	0.107	0.109		0.653	0.703	0.685	
Min	-0.473	-0.559	-0.559		-2.798	-3.966	-3.966	
Max	1.576	1.212	1.576		3.344	3.151	3.344	
Median	0.000	0.000	0.000		0.000	0.000	0.000	

Panel B GAAP EPS actual difference between analysts and I/B/E/S (by broker characteristics)

	DIFFACT_P			*Mean difference test*	*DIFFACT_IBES*			*Mean difference test*
	Top Broker				*Top Broker*			
	Yes	No	Total		Yes	No	Total	
N	696	1144	1840		696	1146	1842	
Mean	0.005	0.005	0.005	0.0004	-0.679	-0.202	-0.382	0.4769
S.d.	0.060	0.051	0.055		11.473	8.070	9.500	
Min	-0.874	-0.852	-0.874		-130.333	-129.667	-130.333	
Max	0.779	1.176	1.176		71.000	107.667	107.667	
Median	0.000	0.000	0.000		0.000	0.002	0.002	

Table 2.7 Descriptive Statistics for Forecast Accuracy and Bias: Non-GAAP EPS

Panel A Non-GAAP Forecast Accuracy

Absolute value of Actual EPS Scaling							
	Variable	N	Mean	S.D.	Min	Max	Median
Min FE matching	*Analyst_minnonGAAPFE*	921	0.585	2.427	0.000	36.667	0.124
Earliest matching	*Analyst_nonGAAPFE*	921	0.661	2.456	0.000	36.667	0.150
	IBESnonGAAPFE	2924	0.399	0.538	0.000	4.831	0.217
	Trimming 400%						
	Variable	N	Mean	S.D.	Min	Max	Median
Min FE matching	*Analyst_minnonGAAPFE*	897	0.274	0.456	0.000	3.571	0.119
Earliest matching	*Analyst_nonGAAPFE*	893	0.331	0.546	0.000	3.636	0.142
	IBESnonGAAPFE	2922	0.396	0.527	0.000	3.934	0.217
	Trimming 300%						
	Variable	N	Mean	S.D.	Min	Max	Median
Min FE matching	*Analyst_minnonGAAPFE*	892	0.257	0.394	0.000	2.946	0.116
Earliest matching	*Analyst_nonGAAPFE*	883	0.297	0.445	0.000	2.969	0.140
	IBESnonGAAPFE	2899	0.372	0.458	0.000	2.994	0.215
	Trimming 200%						
	Variable	N	Mean	S.D.	Min	Max	Median
Min FE matching	*Analyst_minnonGAAPFE*	882	0.232	0.320	0.000	1.932	0.115
Earliest matching	*Analyst_nonGAAPFE*	864	0.252	0.324	0.000	1.932	0.138
	IBESnonGAAPFE	2856	0.341	0.378	0.000	1.992	0.207
	Trimming 100%						
	Variable	N	Mean	S.D.	Min	Max	Median
Min FE matching	*Analyst_minnonGAAPFE*	837	0.172	0.182	0.000	0.985	0.103
Earliest matching	*Analyst_nonGAAPFE*	820	0.193	0.198	0.000	0.987	0.121
	IBESnonGAAPFE	2667	0.263	0.236	0.000	0.997	0.185
Stock Price Scaling							
	Variable	N	Mean	S.D.	Min	Max	Median
Min FE matching	*Analyst_minnonGAAPFE_sp*	921	0.024	0.045	0.000	0.812	0.011
Earliest matching	*Analyst_nonGAAPFE_sp*	921	0.029	0.054	0.000	0.812	0.013
	IBESnonGAAPFE_sp	2924	0.041	0.062	0.000	0.511	0.021

Table 2.7 (continued)

Panel B Non-GAAP Forecast Bias

Absolute value of Actual EPS Scaling							
	Variable	N	Mean	S.D.	Min	Max	Median
Min FE matching	*Analyst_nonGAAPbias_min*	921	-0.422	2.399	-36.667	3.571	-0.048
Earliest matching	*Analyst_nonGAAPbias*	921	-0.510	2.492	-36.667	7.540	-0.069
	IBESnonGAAPbias	2924	-0.075	0.665	-4.204	4.831	-0.010
	Trimming 400%						
	Variable	N	Mean	S.D.	Min	Max	Median
Min FE matching	*Analyst_nonGAAPbias_min*	897	-0.140	0.521	-3.440	3.571	-0.038
Earliest matching	*Analyst_nonGAAPbias*	893	-0.192	0.609	-3.469	3.636	-0.065
	IBESnonGAAPbias	2922	-0.075	0.655	-3.789	3.934	-0.010
	Trimming 300%						
	Variable	N	Mean	S.D.	Min	Max	Median
Min FE matching	*Analyst_nonGAAPbias_min*	892	-0.130	0.461	-2.946	2.261	-0.038
Earliest matching	*Analyst_nonGAAPbias*	883	-0.173	0.506	-2.969	1.404	-0.058
	IBESnonGAAPbias	2899	-0.059	0.587	-2.989	2.994	-0.009
	Trimming 200%						
	Variable	N	Mean	S.D.	Min	Max	Median
Min FE matching	*Analyst_nonGAAPbias_min*	882	-0.110	0.390	-1.932	1.404	-0.037
Earliest matching	*Analyst_nonGAAPbias*	864	-0.125	0.391	-1.932	1.404	-0.054
	IBESnonGAAPbias	2856	-0.048	0.506	-1.992	1.979	-0.008
	Trimming 100%						
	Variable	N	Mean	S.D.	Min	Max	Median
Min FE matching	*Analyst_nonGAAPbias_min*	837	-0.057	0.267	-0.988	0.928	-0.026
Earliest matching	*Analyst_nonGAAPbias*	820	-0.073	0.267	-0.987	0.928	-0.041
	IBESnonGAAPbias	2667	-0.038	0.351	-0.997	0.981	-0.005
Stock Price Scaling							
	Variable	N	Mean	S.D.	Min	Max	Median
Min FE matching	*Analyst_nonGAAPbias_min_sp*	921	-0.012	0.050	-0.812	0.17	-0.004
Earliest matching	*Analyst_nonGAAPbias_sp*	921	-0.015	0.059	-0.812	0.332	-0.006
	IBESnonGAAPbias_sp	2924	0.003	0.075	-0.511	0.492	-0.001

This table provides descriptive statistics for non-GAAP forecast accuracy and bias based on different measurements and matching methods. I first present the forecast accuracy and bias, scaled by the absolute value of actual EPS. I further report the forecast accuracy and bias scaled by stock price. Panel A presents non-GAAP forecast accuracy. *Analyst_minnonGAAPFE* identifies analysts' own minimum non-GAAP forecast error. *Analyst_nonGAAPFE* identifies analysts' own non-GAAP forecast error calculated using the earliest analysts' unique actual after the earnings announcement date. *IBESnonGAAPFE* identifies non-GAAP forecast error calculated using I/B/E/S data for the same banks and forecast announcement periods. Panel B presents non-GAAP forecast bias. *Analyst_nonGAAPbias_min* identifies analysts' unique non-GAAP bias using the same sample with the minimum non-GAAP forecast error. *Analyst_nonGAAPbias* identifies analysts' unique non-GAAP forecast bias calculated using the earliest analysts' unique actual I can identify. *IBESnonGAAPbias* identifies non-GAAP forecast bias calculated using I/B/E/S data for the same banks and forecast announcement periods. All variable definitions are presented in Appendix A2.1. Samples are trimmed with alternative rules to exclude extreme forecasts changes.

Table 2.8 Descriptive Statistics for Forecast Accuracy and Bias: GAAP EPS

Panel A GAAP Forecast Accuracy

Absolute value of Actual EPS Scaling							
	Variable	N	Mean	S.D.	Min	Max	Median
Min FE matching	*Analyst_minGAAPFE*	843	2.452	9.274	0.000	148.000	0.284
Earliest matching	*Analyst_GAAPFE*	843	2.612	9.468	0.000	148.000	0.307
	GAAPFE_AnaCom	1105	2.618	8.151	0.000	81.143	0.333
	IBES_GAAPFE	1961	6.664	40.649	0.000	1080.700	0.405
	GAAPFE_IBESCom	1961	3.730	26.211	0.000	1080.700	0.392
	Trimming 400%						
	Variable	N	Mean	S.D.	Min	Max	Median
Min FE matching	*Analyst_minGAAPFE*	741	0.631	0.875	0.000	4.000	0.226
Earliest matching	*Analyst_GAAPFE*	734	0.635	0.860	0.000	4.000	0.236
	GAAPFE_AnaCom	957	0.716	0.951	0.000	4.000	0.248
	IBES_GAAPFE	1653	0.726	0.922	0.000	3.954	0.284
	GAAPFE_IBESCom	1654	0.727	0.948	0.000	3.993	0.274
	Trimming 300%						
	Variable	N	Mean	S.D.	Min	Max	Median
Min FE matching	*Analyst_minGAAPFE*	718	0.535	0.698	0.000	3.000	0.210
Earliest matching	*Analyst_GAAPFE*	714	0.551	0.706	0.000	3.000	0.226
	GAAPFE_AnaCom	917	0.586	0.736	0.000	3.000	0.231
	IBES_GAAPFE	1584	0.605	0.731	0.000	3.000	0.268
	GAAPFE_IBESCom	1573	0.582	0.715	0.000	3.000	0.250
	Trimming 200%						
	Variable	N	Mean	S.D.	Min	Max	Median
Min FE matching	*Analyst_minGAAPFE*	681	0.425	0.522	0.000	2.000	0.191
Earliest matching	*Analyst_GAAPFE*	672	0.428	0.516	0.000	2.000	0.202
	GAAPFE_AnaCom	853	0.443	0.530	0.000	2.000	0.196
	IBES_GAAPFE	1466	0.454	0.516	0.000	2.000	0.236
	GAAPFE_IBESCom	1468	0.446	0.515	0.000	2.000	0.220
	Trimming 100%						
	Variable	N	Mean	S.D.	Min	Max	Median
Min FE matching	*Analyst_minGAAPFE*	569	0.218	0.218	0.000	1.000	0.145
Earliest matching	*Analyst_GAAPFE*	563	0.227	0.225	0.000	1.000	0.152
	GAAPFE_AnaCom	703	0.225	0.222	0.000	1.000	0.149
	IBES_GAAPFE	1210	0.245	0.232	0.000	1.000	0.168
	GAAPFE_IBESCom	1215	0.238	0.231	0.000	1.000	0.164
Stock Price Scaling							
	Variable	N	Mean	S.D.	Min	Max	Median
Min FE matching	*Analyst_minGAAPFE_sp*	842	0.049	0.076	0.000	0.812	0.024
Earliest matching	*Analyst_GAAPFE_sp*	842	0.049	0.075	0.000	0.812	0.024
	GAAPFE_AnaCom_sp	1103	0.051	0.073	0.000	0.804	0.026
	IBES_GAAPFE_sp	1961	0.069	0.126	0.000	2.937	0.032
	GAAPFE_IBESCom_sp	1961	0.070	0.128	0.000	2.937	0.031

Table 2.8 (continued)

Panel B GAAP Forecast Bias

	Variable	N	Mean	S.D.	Min	Max	Median
Min FE matching	*Analyst_GAAPbias_min*	843	-2.329	9.306	-148.000	9.600	-0.242
Earliest matching	*Analyst_GAAPbias*	843	-2.482	9.503	-148.000	9.600	-0.261
	GAAPbias_AnaCom	1105	-2.490	8.191	-81.143	5.333	-0.283
	IBES_GAAPbias	1961	-5.949	40.760	-1080.700	127.000	-0.328
	GAAPbias_IBESCom	1961	-3.592	26.230	-1080.700	8.185	-0.322
	Trimming 400%						
	Variable	N	Mean	S.D.	Min	Max	Median
Min FE matching	*Analyst_GAAPbias_min*	741	-0.533	0.938	-4.000	3.529	-0.178
Earliest matching	*Analyst_GAAPbias*	734	-0.539	0.924	-4.000	3.529	-0.188
	GAAPbias_AnaCom	957	-0.579	1.040	-4.000	3.729	-0.188
	IBES_GAAPbias	1653	-0.577	1.022	-3.954	3.714	-0.229
	GAAPbias_IBESCom	1654	-0.587	1.041	-3.993	3.714	-0.211
	Trimming 300%						
	Variable	N	Mean	S.D.	Min	Max	Median
Min FE matching	*Analyst_GAAPbias_min*	718	-0.443	0.760	-3.000	2.000	-0.167
Earliest matching	*Analyst_GAAPbias*	714	-0.462	0.767	-3.000	2.000	-0.182
	GAAPbias_AnaCom	917	-0.460	0.821	-3.000	2.429	-0.176
	IBES_GAAPbias	1584	-0.477	0.820	-3.000	3.000	-0.215
	GAAPbias_IBESCom	1573	-0.457	0.801	-3.000	2.875	-0.188
	Trimming 200%						
	Variable	N	Mean	S.D.	Min	Max	Median
Min FE matching	*Analyst_GAAPbias_min*	681	-0.328	0.588	-2.000	2.000	-0.139
Earliest matching	*Analyst_GAAPbias*	672	-0.334	0.582	-2.000	2.000	-0.148
	GAAPbias_AnaCom	853	-0.338	0.602	-2.000	1.954	-0.149
	IBES_GAAPbias	1466	-0.346	0.595	-2.000	2.000	-0.178
	GAAPbias_IBESCom	1468	-0.331	0.595	-2.000	2.000	-0.158
	Trimming 100%						
	Variable	N	Mean	S.D.	Min	Max	Median
Min FE matching	*Analyst_GAAPbias_min*	569	-0.128	0.280	-1.000	0.955	-0.092
Earliest matching	*Analyst_GAAPbias*	563	-0.141	0.287	-1.000	0.955	-0.105
	GAAPbias_AnaCom	703	-0.144	0.281	-1.000	0.956	-0.100
	IBES_GAAPbias	1210	-0.153	0.300	-1.000	1.000	-0.115
	GAAPbias_IBESCom	1215	-0.138	0.301	-1.000	0.999	-0.096
Stock Price Scaling							
	Variable	N	Mean	S.D.	Min	Max	Median
Min FE matching	*Analyst_GAAPbias_min_sp*	842	-0.042	0.080	-0.812	0.449	-0.020
Earliest matching	*Analyst_GAAPbias_sp*	842	-0.042	0.079	-0.812	0.449	-0.021
	GAAPbias_AnaCom_sp	1103	-0.043	0.077	-0.804	0.449	-0.022
	IBES_GAAPbias_sp	1961	-0.062	0.130	-2.937	0.389	-0.027
	GAAPbias_IBESCom_sp	1961	-0.063	0.131	-2.937	0.388	-0.026

This table provides descriptive statistics for GAAP forecast accuracy and bias based on different measurements and matching methods. I first present the forecast accuracy and bias, scaled by the absolute value of the actual. I further report the forecast accuracy and bias scaled by stock price. Panel A presents GAAP forecast accuracy. *Analyst_minGAAPFE* identifies analysts' unique minimum GAAP forecast error. *Analyst_GAAPFE* identifies analysts' unique GAAP forecast error calculated using the earliest analysts' unique actual I can identify. *GAAPFE_AnaCom* identifies GAAP forecast error calculated using unique' forecast and company reported actual EPS. *IBES_GAAPFE* identifies GAAP forecast error calculated using I/B/E/S data for the same banks and forecast announcement periods. *GAAPFE_IBESCom* identifies GAAP forecast error calculated using I/B/E/S forecast data and company reported actual EPS. Panel B presents GAAP forecast bias. *Analyst_GAAPbias_min* identifies analysts' unique GAAP bias using the same sample with the minimum GAAP forecast error. *Analyst_GAAPbias* identifies analysts' unique GAAP forecast bias calculated using the earliest analysts' unique actual I can identify. *GAAPbias_AnaCom* identifies GAAP forecast bias calculated using unique' forecast and company reported actual EPS. *IBES_GAAPbias* identifies GAAP forecast bias calculated using I/B/E/S data for the same banks and forecast announcement periods. *GAAPbias_IBESCom* identifies GAAP forecast error calculated using I/B/E/S forecast data and company reported actual EPS. All variable definitions are presented in Appendix A2.1. The samples are trimmed with alternative trimming rules to exclude extreme forecasts changes.

Table 2.9 Tests of Forecast Rationality

Panel A Non-GAAP EPS (Stock price scaling)

		α_0	t-Statistics	α_1	t-Statistics	R-Squared	N	Chow test $\alpha_0^{Ana} = \alpha_0^{IBES}$	Chow test $\alpha_1^{Ana} = \alpha_1^{IBES}$
No Trimming	Analyst_own	-0.006*	-1.87	0.896***	-3.44	48.79%	921	651.8***	530.37***
	IBES	0.086***	48.29	0.165***	-55.60	3.98%	2924		
Trimming 400%	Analyst_own	-0.005	-1.51	0.903***	-3.20	49.94%	893	621.6***	533.39***
	IBES	0.086***	48.07	0.166***	-55.29	3.99%	2922		
Trimming 300%	Analyst_own	-0.006*	-1.85	0.920***	-2.63	51.23%	883	600.9***	514.19***
	IBES	0.084***	45.78	0.188***	-51.76	4.73%	2899		
Trimming 200%	Analyst_own	-0.005	-1.45	0.927**	-2.49	53.73%	864	506.3***	434.57***
	IBES	0.078***	40.02	0.255***	-44.02	7.34%	2856		
Trimming 100%	Analyst_own	-0.001	-0.52	0.958**	-2.55	80.26%	820	314.8***	283.44***
	IBES	0.050***	26.73	0.531***	-28.28	27.83%	2667		

Panel B GAAP EPS (Stock price scaling)

		α_0	t-Statistics	α_1	t-Statistics	R-Squared	N	Chow test $\alpha_0^{Ana} = \alpha_0^{IBES}$	Chow test $\alpha_1^{Ana} = \alpha_1^{IBES}$
No Trimming	Analyst_own	-0.039***	-12.23	0.930**	-2.32	53.22%	842	13.22***	117.58***
	IBES	-0.020***	-6.68	0.446***	-24.86	17.01%	1961		
Trimming 400%	Analyst_own	-0.036***	-10.49	0.979	-0.67	56.80%	733	3.57*	1.02
	IBES	-0.045***	-14.02	0.932**	-2.38	38.81%	1653		
Trimming 300%	Analyst_own	-0.036***	-10.92	1.019	0.61	60.07%	713	3.67*	0.37
	IBES	-0.046***	-14.31	0.991	-0.33	42.42%	1584		
Trimming 200%	Analyst_own	-0.035***	-10.18	1.034	1.06	60.91%	671	3.32*	0.24
	IBES	-0.045***	-13.25	1.010	0.35	43.75%	1466		
Trimming 100%	Analyst_own	-0.019***	-12.53	1.085***	6.64	92.73%	562	13.77***	6.50**
	IBES	-0.027***	-19.16	1.133***	11.45	88.74%	1210		

This table reports the results of regressions of actual EPS on analysts' forecast EPS using different data sets. The equation is specified in Eq. (2.1). The Chow test is used to test whether the coefficients α_0 and α_1 are significantly different for split data sets (hand-collected data and I/B/E/S dataset). Panel A reports the regression results on non-GAAP forecast rationality using stock price scaling. Panel B reports the regression results on GAAP forecast rationality using stock price scaling. The non-GAAP data from analysts' reports has in total 921 observations and I/B/E/S GAAP data has 2,924 observations without trimming. The GAAP data from analysts' reports has in total 842 observations and I/B/E/S non-GAAP data has 1,961 observations without trimming. The samples are trimmed with alternative trimming rules to exclude extreme forecasts errors. The results are presented in different rows for different outlier trimming rules. All variable definitions are presented in Appendix A2.1. Specifically, t-statistics for coefficients α_1 are based on the null hypothesis H_0=1. *, **, *** indicate significance levels (two-sided) of 10%, 5% and 1%, respectively.

Table 2.10 Analysis of Bias and Overreaction

Panel A Regression results for Non-GAAP forecast overreaction

		γ_0	t-Statistics	γ_1	t-Statistics	R-Square	N	Chow test $\gamma_0^{Ana} = \gamma_0^{IBES}$	Chow test $\gamma_1^{Ana} = \gamma_1^{IBES}$
No Trimming	Analyst_own	-0.001	-0.01	0.627***	-45.29	86.34%	918	0.04	3.39*
	IBES	0.018	1.41	0.518***	-28.93	24.91%	2924		
Trimming 400%	Analyst_own	0.060	0.37	0.628***	-44.80	86.58%	890	0.20	3.35*
	IBES	0.018	1.42	0.521***	-28.73	25.01%	2922		
Trimming 300%	Analyst_own	0.063	0.39	0.628***	-44.60	86.62%	880	0.20	2.06
	IBES	0.022*	1.72	0.542***	-27.11	26.28%	2899		
Trimming 200%	Analyst_own	0.099	0.59	0.628***	-44.15	86.66%	861	0.61	0.23
	IBES	0.025**	2.05	0.598***	-23.80	30.58%	2856		
Trimming 100%	Analyst_own	0.277*	1.65	0.629***	-44.76	87.63%	817	6.90***	4.85**
	IBES	0.028***	2.96	0.780***	-15.77	54.12%	2667		

Panel B Regression results for GAAP forecast overreaction

		γ_0	t-Statistics	γ_1	t-Statistics	R-Square	N	Chow test $\gamma_0^{Ana} = \gamma_0^{IBES}$	Chow test $\gamma_1^{Ana} = \gamma_1^{IBES}$
No Trimming	Analyst_own	0.15	0.79	0.340***	-73.87	63.47%	836	1.92	669.5***
	IBES	0.76***	2.74	-0.140	-153.29	15.29%	1961		
Trimming 400%	Analyst_own	0.46**	2.17	0.345***	-69.81	65.13%	727	0.00	140.76***
	IBES	0.428	1.37	0.060***	-51.30	0.66%	1653		
Trimming 300%	Analyst_own	0.51**	2.32	0.345***	-68.95	65.20%	707	5.28**	73.9***
	IBES	-0.413	-1.64	0.546***	-22.00	30.74%	1584		
Trimming 200%	Analyst_own	-0.47***	-9.11	1.011*	1.85	97.59%	665	1.69	12.87***
	IBES	-0.78***	-4.87	0.915***	-5.87	73.22%	1466		
Trimming 100%	Analyst_own	-0.22***	-4.96	1.015***	3.22	98.73%	557	0.81	2.17
	IBES	-0.31***	-4.58	0.999	-0.02	96.17%	1210		

This table reports the regression results of actual changes in EPS on analysts' forecast change in EPS. The equation is specified in Eq. (2.2). The Chow test is used to test whether the coefficients γ_0 and γ_1 are significantly different for split data sets (analyst report data and I/B/E/S dataset). Panel A reports the regression results for non-GAAP forecast overreaction. The non-GAAP data from analysts' reports has in total 918 observations and I/B/E/S non-GAAP data has 2,924 observations without trimming. Panel B reports the regression results for GAAP forecasts. The GAAP data from analysts' reports has in total 836 observations and I/B/E/S GAAP data has in total 1,961 observations without trimming. The samples are trimmed with alternative trimming rules to exclude extreme forecasts errors. The results are presented in different rows using different outlier trimming rules. All variable definitions are presented in Appendix A2.1. Specifically, t-statistics for coefficients γ_1 are based on the null hypothesis H_0=1. *, **, *** indicate significance levels (two-sided) of 10%, 5% and 1%, respectively.

Table 2.11 Forecast errors and actual EPS difference between analysts and I/B/E/S

Panel A Non-GAAP forecast errors and actual EPS difference between analysts and IBES

	(1) *FE*	(2) *FE*	(3) *FE*
PREACT_DIFF	-0.152***	-0.149***	-0.149***
	(-7.44)	(-6.83)	(-6.60)
Constant	0.027***	0.032***	0.031*
	(15.78)	(5.67)	(1.78)
Bank. FE	N	Y	Y
Brokers. FE	N	N	Y
Observations	918	918	918
R-squared	0.057	0.0917	0.119

Panel B GAAP forecast errors and actual EPS difference between analysts and IBES

	(1) *FE*	(2) *FE*	(3) *FE*
PREACT_DIFF	0.081	0.121	0.120
	(0.83)	(1.23)	(1.19)
Constant	0.049***	0.072***	0.053*
	(18.48)	(8.43)	(1.91)
Bank. FE	N	Y	Y
Brokers. FE	N	N	Y
Observations	836	836	836
R-squared	0.0008	0.1117	0.1411

This table reports the regression results of forecast accuracy on actual EPS difference between analysts and IBES for the previous fiscal year. The forecast accuracy is measured by the absolute value of difference between analysts' actual EPS and forecast EPS, scaled by stock price taken from analysts' reports. The actual EPS difference between analysts and IBES for the previous fiscal year is scaled by stock price taken from analysts' reports as well. The equation is specified in Eq. (2.3). Panel A reports the regression results for non-GAAP data. Panel B reports the regression results for GAAP data. Column (1) shows the results without considering any fixed effects. Column (2) shows the results with bank fixed effects and column (3) shows the results with both bank and brokers fixed effects. All variable definitions are presented in Appendix A2.1. t-statistics are reported in parentheses *, **, *** indicate significance levels (two-sided) of 10%, 5% and 1%, respectively.

Table 2.12 GAAP Forecast errors and actual Non-GAAP EPS difference between analysts and I/B/E/S

	(1) *FE_GAAP*	(2) *FE_GAAP*	(3) *FE_GAAP*
*PREACT_*	-0.192*	-0.155	-0.167
DIFF_NonGAAP	(-1.95)	(-1.33)	(-1.25)
Constant	0.050***	0.065***	0.050***
	(6.00)	(10.93)	(8.15)
Bank. FE	N	Y	Y
Brokers. FE	N	N	Y
Observations	756	756	756
R-squared	0.0458	0.1231	0.1532

This table reports the regression results of GAAP forecast accuracy on non-GAAP actual EPS difference between analysts and IBES in the previous fiscal year. The forecast accuracy is measured by the absolute value of difference between analysts' actual GAAP EPS and forecast GAAP EPS, scaled by stock price taken from analysts' reports. The actual non-GAAP EPS difference between analysts and IBES for the previous fiscal year is scaled by stock price taken from analysts' reports as well. Column (1) shows the results without considering any fixed effects. Column (2) shows the results with bank fixed effects and column (3) shows the results with both bank and brokers fixed effects. All variable definitions are presented in Appendix A2.1. Standard errors are clustered at the bank level. t-statistics are reported in parentheses *, **, *** indicate significance levels (two-sided) of 10%, 5% and 1%, respectively.

Table 2.13 Persistence test of analyst-I/B/E/S differences in actual EPS

Panel A Non-GAAP EPS difference between analysts and I/B/E/S

	(1) *DIFFACT_P*	(2) *DIFFACT_P*	(3) *DIFFACT_P*
PREACT_DIFF	0.284***	0.132***	0.120***
	(10.47)	(4.20)	(3.75)
Constant	-0.011***	-0.011***	0.120***
	(-3.17)	(-3.38)	(6.51)
Year. FE	N	N	Y
Brokers. FE	N	Y	Y
Observations	635	635	635
R-squared	0.035	0.035	0.155

Panel B GAAP EPS difference between analysts and I/B/E/S

	(1) *DIFFACT_P*	(2) *DIFFACT_P*	(3) *DIFFACT_P*
PREACT_DIFF	0.031*	0.010	0.015
	(2.29)	(0.68)	(1.04)
Constant	-0.005***	0.005***	0.001
	(4.24)	(4.28)	(0.22)
Year. FE	N	N	Y
Brokers. FE	N	Y	Y
Observations	586	586	586
R-squared	0.001	0.001	0.037

This table reports the regression results of actual EPS difference between analysts and IBES on the actual EPS difference for the previous fiscal year. The actual EPS difference between analysts and IBES is scaled by stock price taken from analysts' reports. The equation is specified in Eq. (2.4). Panel A reports the regression results for non-GAAP data. Panel B reports the regression results for GAAP data. Column (1) shows the results without considering any fixed effects. Column (2) shows the results with brokers fixed effects and column (3) shows the results with both year and brokers fixed effects. All variable definitions are presented in Appendix A2.1. t-statistics are reported in parentheses *, **, *** indicate significance levels (two-sided) of 10%, 5% and 1%, respectively.

Appendices of Chapter 2

Appendix A2.1 Variable Definitions

Variables	Definition	Measurement
DIFFACT_P	Difference between analysts' unique actual EPS and I/B/E/S actual EPS scaled by stock price taken from the analysts' report.	$\frac{A_{i,j,t}^{Ana} - A_{i,j,t}^{IBES}}{Price_{Ana}}$
DIFFACT_IBES	Difference between analysts' unique actual EPS and I/B/E/S actual EPS scaled by the absolute value of the I/B/E/S actual EPS.	$\frac{A_{i,j,t}^{Ana} - A_{i,j,t}^{ibes}}{\lvert A_{i,j,t}^{ibes} \rvert}$
Analyst_minnonGAAPFE	The analysts' non-GAAP forecast error measured by the absolute value of the difference between analysts' non-GAAP actual EPS and analysts' non-GAAP forecast EPS over the unique non-GAAP actual EPS. The analysts' non-GAAP actual EPS here is the actual non-GAAP EPS that minimizes the forecast error when analysts in the same broker report multiple actual EPS for the same bank and the same year.	$\left\lvert \frac{A_{i,j,t}^{Anamin} - F_{i,j,t}^{Ana}}{A_{i,j,t}^{min}} \right\rvert$
Analyst_nonGAAPFE	The analysts' non-GAAP forecast error measured by the absolute value of the difference between analysts' unique non-GAAP actual EPS and non-GAAP forecast EPS over the analysts' non-GAAP actual EPS. The analysts' non-GAAP actual EPS here refers to the actual non-GAAP EPS that analysts report just after the earnings announcement date of the bank. It is the earliest analysts' unique actual I can identify.	$\left\lvert \frac{A_{i,j,t}^{Ana} - F_{i,j,t}^{Ana}}{A_{i,j,t}^{Ana}} \right\rvert$
IBESnongaapFE	The I/B/E/S analysts' non-GAAP forecast error measured by the absolute value of the difference between analysts' non-GAAP actual EPS and non-GAAP forecast EPS over the non-GAAP actual EPS from the I/B/E/S database.	$\left\lvert \frac{A_{i,j,t}^{ibes} - F_{i,j,t}^{ibes}}{A_{i,j,t}^{ibes}} \right\rvert$
Analyst_nonGAAPbias_min	The analysts' non-GAAP forecast bias measured by the difference between analysts' non-GAAP actual EPS and non-GAAP forecast EPS over the absolute value of analysts' non-GAAP actual EPS. The analysts' non-GAAP actual EPS here refers to the actual non-GAAP EPS that minimizes the forecast error when analysts in the same broker report multiple actual EPS for the same bank and the same year.	$\frac{A_{i,j,t}^{Anamin} - F_{i,j,t}^{Ana}}{\lvert A_{i,j,t}^{Anamin} \rvert}$
Analyst_nonGAAPbias	The analysts' non-GAAP forecast bias measured by the difference between analysts' non-GAAP actual EPS and non-GAAP forecast EPS over the absolute value of analysts' non-GAAP actual EPS. The analysts' non-GAAP actual here refers to the actual non-GAAP EPS that analysts report just after the earnings announcement date of the bank. It is the earliest analysts' unique actual I can identify.	$\frac{A_{i,j,t}^{Ana} - F_{i,j,t}^{Ana}}{\lvert A_{i,j,t}^{Ana} \rvert}$

IBESnonGAAPbias	The I/B/E/S analysts' non-GAAP forecast bias measured by the difference between analysts' non-GAAP actual EPS and non-GAAP forecast EPS over the absolute value of non-GAAP actual EPS from the I/B/E/S database.	$\frac{A_{i,j,t}^{IBES} - F_{i,j,t}^{IBES}}{\lvert A_{i,j,t}^{ibes} \rvert}$
Analyst_minGAAPFE	The analysts' GAAP forecast error measured by the absolute value of the difference between analysts' GAAP actual EPS and analysts' GAAP forecast EPS over the unique GAAP actual EPS. The analysts' GAAP actual EPS here is the actual GAAP EPS that minimizes the forecast error when analysts in the same broker report multiple actual EPS for the same bank and the same year.	$\left\lvert \frac{A_{i,j,t}^{Anamin} - F_{i,j,t}^{Ana}}{A_{i,j,t}^{Anamin}} \right\rvert$
Analyst_GAAPFE	The analysts' GAAP forecast error measured by the absolute value of the difference between analysts' unique GAAP actual EPS and GAAP forecast EPS over the analysts' GAAP actual EPS. The analysts' GAAP actual EPS here refers to the actual GAAP EPS that analysts report just after the earnings announcement date of the bank. It is the earliest analysts' unique actual I can identify.	$\left\lvert \frac{A_{i,j,t}^{Ana} - F_{i,j,t}^{Ana}}{A_{i,j,t}^{Ana}} \right\rvert$
GAAPFE_AnaCom	The analysts' GAAP forecast error measured by the absolute value of the difference between company reported GAAP actual EPS and analysts' forecast GAAP EPS over the company reported GAAP actual EPS.	$\left\lvert \frac{A_{i,j,t}^{com} - F_{i,j,t}^{Ana}}{A_{i,j,t}^{com}} \right\rvert$
IBES_GAAPFE	The I/B/E/S analysts' GAAP forecast error measured by the absolute value of the difference between analysts' GAAP actual EPS and GAAP forecast EPS over the GAAP actual EPS from the I/B/E/S database.	$\left\lvert \frac{A_{i,j,t}^{IBES} - F_{i,j,t}^{IBES}}{A_{i,j,t}^{ibes}} \right\rvert$
GAAPFE_IBESCom	The analysts' GAAP forecast error measured by the absolute value of the difference between company reported GAAP actual EPS and analysts' GAAP forecast from the I/B/E/S database over the company reported GAAP actual EPS.	$\left\lvert \frac{A_{i,j,t}^{Com} - F_{i,j,t}^{ibes}}{A_{i,j,t}^{Com}} \right\rvert$
Analyst_GAAPbias_min	The analysts' GAAP forecast bias measured by the difference between analysts' GAAP actual EPS and GAAP forecast EPS over the absolute value of analysts' GAAP actual EPS. The analysts' GAAP actual EPS here refers to the actual GAAP EPS that minimizes the forecast error when analysts in the same broker report multiple actual EPS for the same bank and the same year.	$\frac{A_{i,j,t}^{Anamin} - F_{i,j,t}^{Ana}}{\lvert A_{i,j,t}^{Anamin} \rvert}$
Analyst_GAAPbias	The analysts' GAAP forecast bias measured by the difference between analysts' GAAP actual EPS and GAAP forecast EPS over the absolute value of analysts' GAAP actual EPS. The analysts' GAAP actual here refers to the actual GAAP EPS that analysts report just after the earnings announcement date of the bank. It is the earliest analysts' unique actual I can identify.	$\frac{A_{i,j,t}^{Ana} - F_{i,j,t}^{Ana}}{\lvert A_{i,j,t}^{Ana} \rvert}$
GAAPbias_AnaCom	The analysts' GAAP forecast bias measured by the difference between company reported GAAP actual EPS and analysts' GAAP forecast over the absolute value of company reported GAAP actual EPS.	$\frac{A_{i,j,t}^{Com} - F_{i,j,t}^{Ana}}{\lvert A_{i,j,t}^{Com} \rvert}$

IBES_GAAPbias	The I/B/E/S analysts' GAAP forecast bias measured by the difference between analysts' GAAP actual EPS and GAAP forecast EPS over the absolute value of GAAP actual EPS from the I/B/E/S database.	$\frac{A_{i,j,t}^{IBES} - F_{i,j,t}^{IBES}}{\left\|A_{i,j,t}^{ibes}\right\|}$
GAAPbias_IBESCom	The analysts' GAAP forecast bias measured by the difference between company reported GAAP actual EPS and analysts' GAAP forecast from the I/B/E/S database over the absolute value of company reported GAAP actual.	$\frac{A_{i,j,t}^{Com} - F_{i,j,t}^{IBES}}{\left\|A_{i,j,t}^{Com}\right\|}$
AC	Actual change measured by the difference between actual EPS for bank j year t and actual EPS for bank j year t-1 over absolute value of actual EPS for bank j year t-1.	$\frac{A_{i,j,t} - A_{i,j,t-1}}{\left\|A_{i,j,t-1}\right\|}$
FC	Forecast change measured by as the difference between analysts' forecast EPS for bank j year t and actual EPS for bank j year t-1 over the absolute value of actual EPS for bank j year t-1.	$\frac{F_{i,j,t} - A_{i,j,t-1}}{\left\|A_{i,j,t-1}\right\|}$
FE	Analysts forecast error measured by the absolute value of difference between analysts' actual EPS and forecast EPS, scaled by the stock price taken from the analysts' reports.	$\frac{\left\|A_{i,j,t}^{Ana} - F_{i,j,t}^{Ana}\right\|}{Price_{Ana}}$
FE_GAAP	Analysts forecast error measured by the absolute value of difference between analysts' actual GAAP EPS and forecast GAAP EPS, scaled by the stock price taken from the analysts' reports.	$\frac{\left\|A_{i,j,t}^{Ana\_GAAP} - F_{i,j,t}^{Ana\_GAAP}\right\|}{Price_{Ana}}$
PREACT_DIFF	Difference between analysts' unique actual EPS and I/B/E/S actual EPS for year t-1, scaled by stock price taken from the analysts' report.	$\frac{A_{i,j,t-1}^{Ana} - A_{i,j,t-1}^{IBES}}{Price_{Ana}}$
PREACT_DIFF_NonGAAP	Difference between analysts' unique actual non-GAAP EPS and I/B/E/S actual non-GAAP EPS for year t-1, scaled by stock price taken from the analysts' report.	$\frac{A_{i,j,t-1}^{Ana\_NGAAP} - A_{i,j,t-1}^{ibes\_NGAAP}}{Price_{Ana}}$

Chapter 3

Assessing information content and post earnings announcement drift (PEAD) using GAAP and Non-GAAP earnings

Abstract

This study investigates the market reactions to various definitions of earnings surprises including GAAP earnings surprises, non-GAAP earnings surprises and GAAP earnings surprises with measurement error in both short-term and long-term in an international setting. I find that investors perceive non-GAAP earnings to be more informative than GAAP earnings at the earnings announcement date. However, previously identified GAAP earnings surprises with measurement error downwardly bias market responses to GAAP earnings. The error component (forecast exclusions) provides incremental useful information in addition to the information captured in GAAP forecasts. After correcting the measurement error, my analyses of PEAD reveals that investors may not utilise the information captured by GAAP earnings efficiently compared to that of non-GAAP earnings.

3.1 Introduction

Sell-side analyst reported earnings tracked by the Institutional Brokers Estimate System (I/B/E/S) are often considered as archetypal non-GAAP earnings. These non-GAAP earnings are modified by excluding items from GAAP measures. Exclusion items may be non-recurring (i.e., transitory) items, such as restructuring costs, or recurring items such as stock-based compensation (Bradshaw and Sloan, 2002). Whether certain components of GAAP earnings are subject to exclusions is based on individual analyst' judgements (Baik et al., 2009). Though non-GAAP earnings are arguably metrics of companies' 'core performance' and hence more useful for predicting future performance (Lougee and Marquardt, 2004), critics allege that analysts' self-interest and economic incentives underlie analysts' selective treatment of excluding items (Lambert, 2004; Gullapalli, 2005). Given that non-GAAP earnings are not consistently defined, close attention is needed when interpreting forecast surprises and forecast errors are derived from non-GAAP earnings (Lambert, 2004).

Earlier studies explored the relative informativeness of non-GAAP earnings compared to GAAP earnings in response to the substantial increase in analysts' emphasis on non-GAAP earnings (Bentley et al., 2018). Evidence generally suggests that non-GAAP earnings are more strongly associated with short-term cumulative abnormal returns than GAAP earnings (Bradshaw and Sloan, 2002; Bhattacharya et al., 2003; Bradshaw et al., 2018). However, because GAAP earnings forecasts have not been historically available on I/B/E/S, prior studies measure GAAP earnings surprises as the difference between *actual GAAP* earnings per share (EPS) and *forecast non-GAAP* EPS (e.g., Bradshaw, 2003; Berger, 2005; Cohen, Hann and Ogneva, 2007). According to Bradshaw et al. (2018), this traditional way of identifying GAAP forecast error is subject to significant measurement error. This raises concerns about possible bias in prior conclusions that investors perceive non-GAAP earnings to be more informative than GAAP earnings (Berger, 2005; Cohen, Hann and Ogneva, 2007). When correcting for this type of measurement error, Bradshaw et al. (2018) find that the GAAP forecast error measured with noise biases downward the market reaction to GAAP earnings, however, investors still show a greater response to non-GAAP earnings compared to GAAP earnings.

The inference about the relative informativeness of non-GAAP and GAAP earnings forecasts using samples of U.S. firms cannot directly be generalised to other institutional settings. This is because analysts' forecast and analysts' disclosure of non-GAAP measures vary with the forecast environment and the accounting practice in each institutional environment (Capstaff et al., 2001, Marques, 2006), thus analysts' forecast accuracy are affected by these factors. For example, analysts' forecast accuracy can be affected by the quality of accounting disclosures (Baldwin, 1984). When comparing the financial disclosure effectiveness across the UK, the US and four European countries, Saudagaran and Biddle (1992) find that the UK exhibits the highest quality of disclosure. Therefore, in this chapter, I first explore the relative informativeness of non-GAAP and GAAP earnings using the corrected measurement of GAAP earnings surprises in European sample.

In addition to short window market reactions to earnings surprises, studies also explore long-term post earnings announcement abnormal returns. Post earnings announcement drift (PEAD) refers to the tendency for stock prices to continue to drift in the direction of earnings surprises for the subsequent weeks after an earnings announcement and is one of the most robust market anomalies (Fama, 1998). According to Livnat and Mendenhall (2006), understanding which form of earnings surprises provides the greatest drift is crucial for examining market anomalies.

Prior studies have examined the magnitude and patterns of PEAD using analysts' non-GAAP forecast errors, time series models and Compustat earnings surprises (Doyle, Lundholm and Soliman, 2003; Livnat and Mendenhall, 2006). Livnat and Mendenhall (2006) show that the drift is larger when using analysts' non-GAAP forecast error compared to a time-series forecast error. Nevertheless, most results are based on U.S. samples. A study by Huang, Li and Wang (2015) provides insights on PEAD in the international setting. Using the 2005 mandatory adoption of International Financial Reporting Standards (IFRS) as an exogenous information shock, they find that PEAD, calculated using analysts' non-GAAP earnings surprises, declines after the information shock.

In this chapter, I correct the measurement error identified by Bradshaw et al. (2018) by using I/B/E/S analysts' GAAP forecast and actual data. I then provide a comparison between non-GAAP based and GAAP based short term market reaction and long-term drift in an international setting.

My analysis reveals that the previously identified GAAP earnings surprises tend to overestimate the magnitude of GAAP earnings surprises by 20% compared to the correctly measured GAAP earnings surprises. When I recalibrate the measurement in forecast error in prior studies of investors' preference for GAAP and non-GAAP earnings, my findings suggest that investors still find non-GAAP earnings to be more informative than GAAP earnings at the earnings announcement date. Thus, this type of measurement error does not result in biased or incorrect inferences in assessing investors' preference for non-GAAP earnings. However, further investigation of investors' responses to different definitions of GAAP earnings surprises indicates that using previously defined GAAP earnings surprises results in an underestimation of investors' attention to GAAP earnings. In summary, when more precisely measured, GAAP earnings are more influential than prior research concludes, but are still not as important as non-GAAP earnings.

By decomposing GAAP earnings surprises with measurement error into two components—the corrected GAAP earnings surprise and the forecast exclusions (i.e., the error part), I find that the forecast exclusions are positively associated with short-term cumulative abnormal return (CAR). This indicates that the error component provides incrementally useful information, in addition to the information found in GAAP forecasts. This result corroborates Whipple's (2015) argument that exclusion items are informative and indicates that previously identified investor preference for non-GAAP earnings is partly explained by the measurement error component.

I then turn to longer run reactions to earnings surprises. My investigation of post earnings announcement drift (PEAD) using different measures of earnings surprises reveals that the corrected GAAP-based PEAD is higher than the non-GAAP based PEAD. Specifically, the subsequent quarter return of a hedge portfolio based on GAAP earnings surprise is on average 25% higher than that based on non-GAAP earnings surprise, indicating that investors may not use the information contained in GAAP earnings as efficiently as non-GAAP earnings. This result supports Doyle, Lundholm and Soliman's (2003) finding that markets price the information contained in exclusion items over a long period.

In additional tests, I examine the effect of GAAP losses and the effect of exclusion items on the market reaction to different measures of earnings surprise. GAAP loss-making firms are associated with greater uncertainty (Konstantinidi and Pope, 2016), investors may demand for supplemental information from other sources (Healy and Palepu, 2001). However, analysts are more likely to inflate non-GAAP forecasts when firms report a GAAP loss, considering their incentives to curry favour with managers (McNichols and O`Brien, 1997) and to attract investment banking business (Lin and McNichols, 1998). Leung and Veenman (2018) find that non-GAAP earnings are particularly informative about loss-making firms and thus are highly valued by investors. They derive to the results by comparing firms which report both GAAP and non-GAAP earnings to those report only

GAAP loss. I directly compare market reactions to non-GAAP earnings for profit-making and loss-making firms. My findings suggest that market reactions to non-GAAP earnings at the earnings announcement date are significantly stronger for profit-making firms compared to loss-making firms. One possible explanation for this finding is that investors may perceive non-GAAP reporting to be more aggressive and opportunistic (Kolev, Marquardt, and McVay, 2008; Barth, Beaver, and Landsman, 2012) for GAAP loss firms.

In subsample tests, I partition the sample into firms with positive, zero or negative exclusion items. I find that markets react most strongly to non-GAAP earnings when actual GAAP EPS is larger than actual non-GAAP EPS at the earnings announcement. Baik et al. (2009) argue that analysts have incentives to strategically exclude more income-decreasing items. My findings suggest that the market seems to consider this potentially opportunistic behaviour when reacting to the earnings surprises and value non-GAAP earnings more when analysts exclude income-increasing items. In terms of long-run (i.e., three months) stock returns, I find that investors misprice GAAP earnings on average, while my results are inconclusive with regards to non-GAAP based drift.

My study contributes to the long line of literature on market reactions to analysts' GAAP and non-GAAP forecasts in three ways. First, this chapter complements the study of Bradshaw et al. (2018) by examining the interested market reactions beyond US sample. I analyse an international sample consisting of firms from the UK and ten Eurozone countries. Because different institutional environments might affect analysts' disclosure of non-GAAP financial measures (Marques, 2006) and investors' response to non-GAAP earnings (Yi, 2007), my study provides further evidence of market reactions to non-GAAP and GAAP earnings surprises in an international setting. Second, I adopt an adjusted measure of GAAP earnings surprises that overcomes limitations of the currently widely-used measure. Due to the lack of availability of GAAP forecast data before 2004, prior studies on the informativeness of different earnings definitions and PEAD define GAAP earnings surprise as the difference between GAAP actuals and non-GAAP forecasts, which is now known to give rise to substantial measurement errors. This problem has been extensively identified as a major limitation that may potentially contaminate existing results (Lambert, 2004; Cohen et al., 2007). I overcome this by measuring GAAP earnings surprises as the difference between GAAP actuals and GAAP forecasts from I/B/E/S. Finally, my study provides insight into how the magnitude of post earnings announcement drift varies with GAAP and non-GAAP earnings surprises. Prior research focuses mainly on the time series Compustat-based drift and I/B/E/S-based non-GAAP drift using the US sample (Doyle, Lundholm, and Soliman, 2003; Livnat and Mendenhall, 2006), and there is little evidence on the GAAP based drift and post earnings announcement drift in an international setting. According to Huang, Li and Wang (2015), different institutional environment can affect PEAD in opposite directions, leading to an unclear portrait of PEAD in global studies. For example, countries with better financial reporting environments can facilitate the information processing and therefore lead to lower PEAD. My findings suggest that investors misprice GAAP earnings and market may not fully incorporate information contained in exclusion items at the earnings announcement date.

Section 3.2 reviews the literature related to non-GAAP and GAAP reporting. Section 3.3 develops the hypotheses on both short-term and long-term market reactions to non-GAAP and GAAP earnings. Section 3.4 describes the sample and research design. Section 3.5 provides the descriptive details and results of empirical tests, and section 3.6 concludes.

3.2 Literature Review

In response to the debate about the proliferation of 'non-GAAP' earnings metrics, the relative informativeness of non-GAAP and GAAP earnings has been widely explored. On the one hand, discretion in non-GAAP earnings allows analysts to exclude certain items that are considered as ‘transitory’ and ‘less persistent’ from GAAP earnings. According to Barth et al. (2012), unlike managers who opportunistically inflate earnings by excluding expenses, analysts reportedly exclude extraordinary items to arrive at non-GAAP earnings that better depict firm performance. Thus, they may provide investors with more value relevant information.[10] On the other hand, as non-GAAP earnings are typically unaudited and are subject to inconsistent treatment across firms and over time (Shane and Stock, 2006), critics of non-GAAP earnings and regulators are concerned that the selective information can be misleading to investors.[11] In particular, managers may opportunistically report non-GAAP earnings for purposes including benchmark beating (Doyle, Lundholm, and Soliman 2003; Christensen, Drake, and Thornock, 2014), while analysts may exclude more income-decreasing items to curry favour with managers.

Prior studies generally find that non-GAAP earnings are more informative compared to GAAP earnings at the earnings announcement date (Bhattacharya et al. 2003). Importantly, however, due to the lack of availability of GAAP forecast data before 2004, the GAAP earnings forecasts surprise here, like other studies (Lougee and Marquardt, 2004; Black and Christensen, 2009), are calculated using the difference between GAAP actuals and non-GAAP forecasts. This measurement error problem has been identified as a major limitation that could contaminate existing results (Lambert, 2004; Cohen et al., 2007; Helflin

[10] Bradshaw and Sloan (2002) first compare GAAP and non-GAAP earnings in detail and find that street earnings become the primary determinants of stock prices. Using hand-collected manager reported pro forma earnings and I/B/E/S non-GAAP forecasts, Bhattacharya et al. (2003) further confirm that non-GAAP earnings are better than GAAP earnings in explaining the short-window cumulative return [-1, +1] around the earnings announcement.

[11] In response to concerns about the potential mis-usage of non-GAAP earnings, increasing regulatory requirements of non-GAAP reporting standards have been released. For example, section 401(b) of Sarbanes-Oxley (SOX) (Regulation G), issued by the Securities and Exchange Commission (SEC) in 2003, require managers to reconcile non-GAAP figures to the most directly comparable GAAP measure. In 2005, the Committee of European Securities Regulators (CESR) issued a set of recommendations for the non-GAAP earnings measures, suggesting firms should report these figures ‘in a way that is appropriate and useful for investors’ decision making’.

and Hsu, 2008).

Bradshaw et al. (2018) first document that the 'traditionally identified GAAP forecast error' is subject to a 37% measurement error on average. The misalignment of forecast and actual EPS leads to misclassification of firms that attempt to exclude recurring items to meet or beat analysts' forecasts, and the measurement error further biases previous evidence on firm characteristics associated with meet-or-beat behaviour (Bradshaw et al., 2018). Regarding the informativeness of GAAP earnings using corrected measures of GAAP earnings surprises, their results indicate that whilst the measurement error downwardly biases the coefficient on traditional GAAP earnings surprises, investors still respond more to non-GAAP earnings. In addition, market reactions to non-GAAP earnings surprises are significantly larger when GAAP forecasts are available. Although this study represents a major step forward in the literature, conclusions are based on a U.S sample and short-window market reactions.

The key difference between the previously identified GAAP earnings surprises (*SUE_GAAP_Error*) and the corrected GAAP earnings surprise (*SUE_GAAP*) can be shown in the following equations:

$$SUE\_GAAP = \frac{A_{j,t}^{GAAP} - F_{i,j,t}^{GAAP}}{P} \tag{3.1}$$

$$SUE\_GAAP\_Error = \frac{A_{j,t}^{GAAP} - F_{i,j,t}^{Non-GAAP}}{P} \tag{3.2}$$

$$Diff^{Exclusions} = SUE\_GAAP\_Error - SUE\_GAAP = \frac{F_{i,j,t}^{Exclusions}}{P} \tag{3.3}$$

$A_{j,t}^{GAAP}$ is firm *j*'s actual GAAP earnings per share in period *t*. $F_{i,j,t}^{GAAP}$ is analyst *i*'s forecast of firm *j*'s period *t* GAAP earnings per share. $F_{i,j,t}^{Non-GAAP}$ is analyst *i*'s forecast of firm *j*'s period *t* non-GAAP earnings per share. $F_{i,j,t}^{Exclusions}$ is analyst *i*'s forecast of firm *j*'s period *t* earnings per share for exclusion items. The equation shows that the difference between the previously identified GAAP earnings surprises with measurement error (*SUE_GAAP_Error*) and the corrected GAAP earnings surprise (*SUE_GAAP*) is implicitly the forecast exclusions scaled by stock price ($Diff^{Exclusions}$). Proponents of non-GAAP earnings argue that excluding certain items, especially special items (one-time items such as litigation charge), can create a 'core' performance measure (Elliott et al., 2015) and hence a more informative earnings metric (Bradshaw and Sloan, 2002; Brown and Sivakumar 2003; Heflin et al. 2015). These exclusion items are often related to non-cash items (Whipple, 2015) and thus, are potentially less value relevant.[12] In addition, unlike managers who opportunistically exclude expenses to increase and smooth earnings (Barth, Gow and Taylor, 2012), analysts are often less aggressive (Bentley et al., 2018) and they exclude items in consideration of the earnings predictive ability for firm future performance. Some skeptics of non-GAAP reporting, however, argue that analysts exclude more income-decreasing items in accordance with their own incentives such as generating more investment banking business (Michaely and Womack, 1999) and currying favour with managers (Baik et al., 2009). By decomposing the exclusions into special items (one-off items) and other exclusions (recurring items such as amortization of goodwill and stock-based compensation), Doyle et al. (2003) find that other exclusions are stongly predictive of negative future cash flows. They further explore whether the stock market can fully anticipate this relation and find that investors do not fully incorporate information contained in exclusion items at the earnings announcement date. Other studies also confirm that recurring items excluded are not easily justifiable (Black and Christensen, 2009) and can mislead investors (Landsman et al., 2007). Collectively, these studies suggest that there remains an important debate on the informativeness of forecast exclusions. Whether the

[12] Although this is not necessarily clear ex ante. For instance, see Callen and Segal (2004) for evidence that the accruals (i.e., non-cash) component of earnings is more important than the cash component.

market reaction to previously identified GAAP earnings surprises is partly explained by the forecast exclusions remains an open question.

Most prior studies focus on short-term market reaction to earnings surprises, with fewer studies exploring post earnings announcement abnormal returns in long-term period. Post earnings announcement drift (PEAD), defined as the tendency for stock prices to continue to drift in the direction of earnings surprises for several weeks following an earnings announcement, has been identified as one of the most pervasive capital markets anomalies (Bernard and Thomas, 1990; Mendenhall, 2004). Ball and Brown (1968) evaluate the value of accounting and initially provide empirical evidence that earnings are positively correlated with abnormal stock return, indicating they are informative to investors. However, accounting incomes numbers cannot be transmitted in time and it takes months until the information is fully incorporated into stock prices. They replicate their seminal study in 2019 and find that although the reporting lag has shortened in most countries over the years, and the information environment has improved, this widely acknowledged market anomaly continues in contemporary stock markets around the world (Ball and Brown, 2019).

Livnat & Mendenhall (2006) argue that understanding how different specifications of earnings surprises affect the magnitude and pattern of the drift is essential for understanding the nature of the anomaly. They compare the PEAD for different definitions of earnings surprise and find that the drift is consistently and significantly larger when using analyst forecast errors from I/B/E/S instead of times-series earnings surprises calculated using Compustat data. The analyst forecast error here, like other drift studies (Liang, 2003; Francis et al., 2007), is calculated using the difference between non-GAAP actual and forecast EPS from I/B/E/S. In addition to times-series earnings surprises and I/B/E/S non-GAAP earnings surprises, Doyle, Lundholm and Soliman (2003) focus on the predictive value of expenses excluded from non-GAAP earnings. They find that a profitable one-year, two-year and three-year hedge portfolio can be formed based on decile ranks of exclusion items. Specifically, a hedge portfolio taking a long position in firms in the lowest decile of total exclusions (i.e., non-GAAP is less than GAAP earnings) and a short position in firms in the highest decile of total exclusions (i.e., non-GAAP is more than GAAP earnings) earns on average 11.3% three-year hedge return. They conclude that the initial market reactions to exclusion items (the difference between non-GAAP and GAAP earnings) are far more complete. Nevertheless, the pattern and magnitude of PEAD for earnings surprise measured by GAAP earnings numbers remains an interesting question. As GAAP earnings are more regulated and they perform the disciplining role in forecast evaluation better, understanding GAAP based drift is crucial for understanding the nature of the PEAD.

3.3 Hypotheses Development

Non-GAAP earnings measures are generated when analysts adjust and exclude certain transitory items (such as gains and losses on disposals) from GAAP earnings when forecasting earnings. They can appear in the form of forecasts or earnings realisations. On one hand, because non-GAAP earnings are typically unaudited items and are subject to inconsistent treatment across firms and over time (Shane and Stock, 2006), critics allege that non-GAAP earnings are selective measures and can be misleading to investors (Weil, 2001). Thus, investors may perceive non-GAAP reporting to be more aggressive and opportunistic (Kolev, Marquardt, and McVay, 2008; Barth, Beaver, and Landsman, 2012). GAAP earnings, however, are under audited regime and may play a disciplining' role of accounting. Analysts are less likely to strategically report their GAAP earnings figures, and these GAAP earnings can enhance the comparability of earnings metrics across firms and over time. On the other hand, by their nature, non-GAAP earnings are meant to improve accounting measurement for assessing firm value (Bray, 2001), and by reducing noise in earnings metrics by removing transitory or non-recurring items. They have long been found to be more persistent than GAAP earnings (Bhattacharya et al., 2003) and in some cases, more useful for valuation purposes (Brown and Sivakumar, 2003). In addition, research in decision making has widely documented the intentional cognitive effects on information processing (Tan et al., 2002). That is, individuals may consciously involve a stimulus in their judgement (Frederickson & Miller, 2004). Due to intentional cognitive effects, investors, especially nonprofessional investors, may infer the importance of non-GAAP earnings information (Maines and McDaniel, 2000) given their prominence in earnings announcements (e.g. Plitch, 2002). Thus, investors are predicted to respond more to non-GAAP earnings surprises around the earnings announcement date as they are more prominently featured in earnings announcements (Weil, 2001; Bhattacharya et al., 2003) and may depict a clearer picture of 'core earnings'. To test this prediction, my first hypothesis, stated in the null form is:

H3.1: *There is no difference in the short-term market reaction to GAAP and non-GAAP earnings surprises*

My second hypothesis focuses on exclusion items. In fact, the difference between the previously identified GAAP earnings surprises with measurement error (*SUE_GAAP_Error*) and the corrected GAAP earnings surprise (*SUE_GAAP*) is implicitly the forecast exclusions scaled by stock price. There has been considerable debate over the persistence of, and motivation for, exclusion items. On the one hand, analysts may be reluctant to communicate private information truthfully, especially negative news, due to their incentives to curry favour with managers (McNichols and O`Brien, 1977). In addition, because exclusion items are often transitory (i.e., less persistent), Gu and Chen (2004) find that there is no evidence showing the pricing differential between included items and exclusion items could lead to abnormal future returns. On the other hand, analysts also have incentives to provide reliable and informative earnings measure as their performance is intimately entwined with the incentive of maximizing the value of their forecast to investors. Studies find evidence on analysts excluding certain items to increase their predictive abilities (Barth et al., 2012), and these exclusion items are informative (Whipple, 2015).

Exclusion items can be useful to investors for three reasons. First, exclusion items provide a reconciliation between GAAP and non-GAAP earnings metrics, highlighting the less value-relevant components of earnings. This disaggregated earnings guidance is associated with a richer information environment (Lansford, Lev and Tucker, 2013) that enables investors to better evaluate firm performance. Second, when both GAAP and non-GAAP earnings metrics are available, analysts are less likely to opportunistically adjust non-GAAP earnings forecasts as the disaggregation constrains their ability to do so. As Merkley et al. (2013) state, this could enhance the credibility of the forecast measure. Third, research on decision making demonstrates that individuals make different judgements when additional information is provided (Hoffman and Patton, 1997). Regardless of the relevance to the decision, the presence of information about exclusion items can have unintentional effect on investors' information processing. Frederickson and Miller (2004) find that nonprofessional investors assess a higher stock price when both GAAP and non-GAAP disclosures are available than when only GAAP disclosure is accessible. Thus, the forecasts of exclusion items may provide incrementally useful information over and above that contained in GAAP forecasts. To test this prediction, my second hypothesis, stated in the null form is:

> H3.2: *Forecasts of exclusion items are not related to short-window cumulative abnormal returns.*

Hypothesis 3.1 and 3.2 focus on the short-term market reaction to different definitions of earnings surprises. Despite research showing that non-GAAP earnings measures are widely used for valuation purposes, there are also reasons to expect that the opportunistic use and disclosure of such measures may impede their usefulness to stock market participants. Non-GAAP numbers are typically unaudited and transitory items that are not subject to consistent treatment across firms or over time (Shane and Stock, 2006; Baik et al., 2009). Though investors may not assimilate the GAAP earnings surprise signals at the date of the earnings announcement, they may eventually give more weight to the information implicit in these measures when making decision over longer periods following the announcement. I therefore examine the post earnings announcement drift for both GAAP and non-GAAP earnings surprises. The central difference between GAAP and non-GAAP earnings are exclusion items. According to Doyle, Lundholm and Soliman (2003), certain exclusion items are predictive of long-term future cash flows. Indeed, they recur and consume cash just as regularly as the non-GAAP earnings amounts themselves, which have long been claimed to reflect the 'true performance' of firms. For instance, stock-based compensation is a commonly excluded recurring item that can be used to explain the potential effect of exclusion items on firm value. The options granted to managers can help to reduce the moral hazard problem (Jensen and Meckling, 1976), aligning managers' incentives with the interest of shareholders. Thus, stock-based compensation can positively affect firm value (Hanlon et al., 2003; Cordeiro, Veliyath & Romal, 2007). Alternatively, higher stock-based compensation may negatively affect firm performance as it can be viewed as an opportunity cost (Bodie and et al., 2003). Regardless of the positive or negative effect, this excluded item may still have power in forecasting firm future value. Stock market participants, however, may not fully and promptly incorporate this information. In addition, as shown in the previous chapter, analysts often provide limited explanations of how they arrive at their non-GAAP forecasts.

Based on Bayesian decision theory research (e.g., DeGroot, 1970), investors may place less weight on vague and uncertain information initially, leading to a more muted initial market reaction to the GAAP earnings surprise. Though, in the longer term, as the information environment is enriched and investors digest information from various sources, investors may place more weight on the more regulated GAAP earnings metrics, leading to a higher upward or downward drift in stock prices. Thus, my third hypothesis is stated as follows:

H3.3: *The magnitude of post earnings announcement drift associated with non-GAAP earnings surprises is not different from that associated with GAAP earnings surprises*

3.4 Data and Sample

My sample covers EU firms for the sample period between Jan 2004 and December 2018. My sample starts in 2004 as I/B/E/S began tracking both GAAP earnings forecasts and GAAP earnings actual in 2003. To determine the sample, I first obtain Fiscal year 1 (FY1) non-GAAP forecast earnings per share (EPS) from the *Detail History, Unadjusted* I/B/E/S files from WRDS between 2004 and 2018. I then select the UK and 10 Eurozone countries with the greatest number of firm-year observations. Studies have mainly focused on the U.S. market (Bhattacharya et al. 2003; Livnat and Mendenhall, 2006) with less evidence on the investors' responses to different measures of earnings surprises in an international setting.

The unique institutional environment in the U.S. may limit the generalisation of previous findings to an international setting. For example, new non-GAAP earnings disclosure rules implemented by the U.S. Securities and Exchange Commission (SEC) in 2003 have led to a decline in non-GAAP disclosure and an increased focus on GAAP earnings (Heflin and Hsu, 2008). The implementation of regulation G has also lessened the opportunism in excluding expenses from GAAP earnings (Kolev et al., 2008) and improved the information quality of non-GAAP earnings disclosures in the U.S. (Yi, 2007). Thus, the selection of a sample from European countries and the UK enable me to shed light on investors' perceptions of non-GAAP and GAAP earnings figures in international markets.

I obtain earnings announcement dates from the *Detail History Actuals, Unadjusted* I/B/E/S files. The median estimates of FY1 non-GAAP and GAAP EPS are obtained from *Summary Statistics, Unadjusted* IBES files. The FY0 actual values of non-GAAP and GAAP EPS, and stock price are from the *Summary History Actuals, Pricing and Ancillary, Unadjusted* I/B/E/S file. I use individual stock return index and market return index for each country from Thomson Reuters Datastream to compute daily stock returns and market index returns. Market capitalization and book value of shareholders' equity are also obtained from Datastream.

Next, I use I/B/E/S ticker and RIC code to match the I/B/E/S data to the data from Thomson Reuters Datastream. As RIC code identifies each quote of a company in a specific exchange and currency level, one I/B/E/S ticker could match to multiple RIC codes. In this case, I require the following three criteria to be satisfied to pick up the most favourable RIC code: 1) The main trading market is in the same country as the company is headquartered in; 2) The data availability date in Datastream is the earliest among duplicated I/B/E/S ticker; and 3) The trading volume is the highest for 2018.[13] I then compute all the required variables.

For the dependent variables, the short window CAR is either the equally weighted (*EW_CAR*) or value-weighted (*VW_CAR*) cumulative abnormal return for the three-day window [-1, 1] centred on the earnings announcement date. The subsequent quarter CAR (*EW_PEAD* and *VW_PEAD*) is either the equally weighted or value-weighted cumulative abnormal return on a stock, cumulated from 2 trading days following the announcement to

[13] I find the same results using the average trading volume per year during the sample period 2004-2018. Criteria 1) and 2) can eliminate the majority of duplicated I/B/E/S tickers, though 74 firm RIC codes are picked according to the highest trading volume. These are German stocks trading on both Deutsche Boerse AG and Xetra market.

64 trading days following the announcement (Hung, Li, & Wang, 2015). For the independent variables, earnings surprises (*SUE*) are calculated as the difference between actual EPS and analysts' median forecast EPS, scaled by the stock price no more than 30 days prior to the earnings announcement date. Specifically, I calculate measures of earnings surprise: 1) *SUE_NonGAAP* is defined as the difference between I/B/E/S actual non-GAAP EPS and I/B/E/S forecast non-GAAP EPS, scaled by the stock price no more than 30 days prior to the earnings announcement date; 2) *SUE_GAAP* is defined as the difference between I/B/E/S actual GAAP EPS and I/B/E/S forecast GAAP EPS, scaled by the stock price no more than 30 days prior to the earnings announcement date; 3) *SUE_GAAP_Error* is defined as the difference between I/B/E/S actual GAAP EPS and I/B/E/S forecast non-GAAP EPS, scaled by the stock price no more than 30 days prior to the earnings announcement date. This variable is designed to capture the previously identified GAAP earnings surprises with measurement error.

In the analysis of post earnings announcement drift, earnings surprises are further ranked into 10 portfolios and scaled between 0 and 1. Consistent with Livnat et al. (2006), the decile rank is further subtracted by 0.5 for a zero median. Following Hung, Li, & Wang (2015) and Leung and Veenman (2018), I use firm size, market to book ratio and beta as control variables. These three controls are frequently labelled 'risk factors' and are documented determinants of stock returns (Leung and Veenman, 2018). Firm size (*Size*) is the natural logarithm of market capitalization in millions of Euros at the end of the fiscal year and market to book ratio (*MTB*) is the ratio of market capitalisation to book value of shareholders' equity at the end of the fiscal year. The measure of the volatility of a stock (*Beta*) is the estimated coefficient on the market index return in a CAPM model regression for firm with daily returns in the 90 trading days before the earnings announcement date. Appendix A3.1 provides a detailed definition for these variables.

The sample consists of 20,059 firm-years observations (2,757 firms) with non-missing data required for the equally weighted short-window CARs.[14] For the non-missing data required for the equally weighted subsequent-quarter CARs, the sample consists of 19,492 firm-years observations (2,738 firms).[15] The final sample, as shown in Table 3.1, consists of 2,757 firms from 12 countries. The United Kingdom, France and Germany has the greatest number of firm-year observations, occupying nearly 62% of the whole sample. Portugal, Ireland and Austria have the smallest numbers of unique firms during the sample period.

Insert Table 3.1 about here

3.5 Results

3.5.1 Descriptive Statistics and univariate analysis

Table 3.2 presents the descriptive statistics of main variables. All continuous variables are winsorised at the top and bottom 1% of each distribution to minimize the influence of outliers. On average, non-GAAP earnings surprises (*SUE_NonGAAP*) is higher than the GAAP earnings surprises (*SUE_GAAP*), with the mean values of -1.2% and -3%, respectively.[16] Both the mean and median value of *SUE_GAAP_Error* (-3.6% and -0.2%) are lower than those of *SUE_GAAP* (-3% and -0.1%, respectively), indicating that the previously identified GAAP forecast error with measurement error tends to overestimate the magnitude of GAAP earnings surprise. I employ two alternative measures of the dependent

[14] Due to missing data to calculate weights, the number of firm-years observations is 19,369 (2,702 firms) with non-missing data required for the value-weighted short-window CARs.
[15] The number of firm-years observations is 18,130 (2,684 firms) with non-missing data required for the value-weighted subsequent-quarter CARs.
[16] Earnings surprises are calculated as signed value of the difference between actual EPS and forecast EPS. However, analysts forecast accuracy should be investigated by examining the absolute value of *SUE_GAAP* and *SUE_NonGAAP*. In further untabulated analyses, the mean values of the absolute value of *SUE_GAAP* and *SUE_NonGAAP* are 2.5% and 4.5% respectively. This is not surprising as GAAP forecasts include the prediction of excluding items, which generally include one-off items that are more difficult to predict (Whipple, 2015)

variable, short window CAR [-1, +1], namely equally-weighted CAR (*EW_CAR)* and value-weighted CAR (*VW_CAR)*. Table 3.2 shows that *EW_CAR* and *VW_CAR* have a similar pattern, with the mean value of 0.8% and median value of 0.5%. The mean and median values of subsequent quarter CAR (*EW_PEAD* and *VW_PEAD*) are 3.6% and 3.3%, respectively.

Insert Table 3.2 about here

Table 3.3 reports the results of a country level short-window CAR and subsequent quarter CAR regression. The dependent variables are *EW_CAR*, *EW_PEAD*, *VW_CAR* and *VW_PEAD*, respectively for columns (1) to (4) of every country-year. The highest mean value of *EW_CAR* is 2.08% in Ireland, while the lowest value is -0.47% in Spain, both significant at 1% level. Similar inferences are drawn using *VW_CAR*. The mean values of *EW_CAR* and *VW_CAR*, however, are insignificant in Belgium, Finland, Greece and Netherlands. Columns (2) and (4) shows the post earnings announcement drift (PEAD) in all 12 countries. The highest subsequent quarter equally weighted CAR amounts to 6.05% in Italy, while the lowest is 1.39% in Spain. The mean value of *VW_PEAD* for each country varies between 1.6% and 5.77%, consistent with the country-level PEAD analysis of Hung, Li, & Wang (2015).

Insert Table 3.3 about here

3.5.2 The relative informativeness of Non-GAAP earnings and GAAP earnings

In this section, using short-term market reaction to measure informativeness, I examine whether investors perceive non-GAAP earnings to be more informative compared to GAAP earnings. Three measures of earnings surprise are calculated: 1) non-GAAP earnings surprise (*SUE_NonGAAP)* is defined as the difference between I/B/E/S actual non-GAAP EPS and I/B/E/S forecast non-GAAP EPS, scaled by the stock price no more than 30 days prior to the earnings announcement date; 2) GAAP earnings surprise (*SUE_GAAP)* is defined as the difference between I/B/E/S actual GAAP EPS and I/B/E/S forecast GAAP EPS, scaled by the stock price no more than 30 days prior to the earnings announcement date; and 3) GAAP earnings surprise with error (*SUE_GAAP_Error)* is defined as the difference between I/B/E/S actual GAAP EPS and I/B/E/S forecast non-GAAP EPS, scaled by the stock price no more than 30 days prior to the earnings announcement date. This is also considered as the previously identified GAAP earnings surprise with measurement error (Christensen, 2007; Cohen et al. 2007; Doyle et al., 2013). I then regress the three-day window cumulative abnormal return CAR [-1, 1] surrounding the earnings announcement separately on each defined earnings surprise. Specifically, I estimate the following models:

$$CAR_{[-1,+1]} = \alpha_1 + \beta_1 SUE\_NonGAAP + Controls + Country/year\ fixed\ effect + \varepsilon_1 \quad (3.4)$$

$$CAR_{[-1,+1]} = \alpha_2 + \beta_2 SUE\_GAAP + Controls + Country/year\ fixed\ effect + \varepsilon_2 \quad (3.5)$$

$$CAR_{[-1,+1]} = \alpha_3 + \beta_3 SUE\_Error + Controls + Country/year\ fixed\ effect + \varepsilon_3 \quad (3.6)$$

where $CAR_{[-1,+1]}$ can be either cumulative equally weighted abnormal return (*EW_CAR*) or cumulative value weighted abnormal return (*VW_CAR*) for the three-day window [-1,1] centred on the earnings announcement, *Controls* represents a vector of control variables comprising *Size*, *MTB* and *Beta* to capture the effect of firm characteristics on the CAR. Country and year fixed effects are also included in each of the three regression models.

Table 3.4 presents the results of regressing short-window CAR on different measures of earnings surprises. Columns (1) and (2) present the results from estimating specifications (1) and (2) using $SUE\_NonGAAP$ and SUE_GAAP, respectively. After correcting the measurement error, the estimated coefficient of $SUE\_NonGAAP$ (0.067) is still much higher than the estimated coefficient of SUE_GAAP (0.036), indicating that investors respond more to non-GAAP earnings than to GAAP earnings.[17] These results are robust to using the alternative measure of CAR, VW_CAR as shown in Column (4) and (5) of Table 3.4. All coefficients of $SUE\_NonGAAP$ and SUE_GAAP are statistically significant at 1% level. This result rejects hypothesis 3.1 and reinforces the findings of Bradshaw et al. (2018). Even after correcting for imprecision in the measures of GAAP earnings surprises employed in previous research, the inferences of these studies remain: investors find non-GAAP earnings to be more informative than GAAP earnings.

To further investigate whether the measurement error leads to difference inferences in the investors' response to GAAP earnings, Column (2) and (3) compares the results from estimating specifications (2) and (3) using SUE_GAAP and SUE_GAAP_Error, respectively. The chow test is used to test whether the coefficients on SUE_GAAP and SUE_GAAP_Error are significantly different. The estimated coefficient of SUE_GAAP of 0.036 is slightly higher than the coefficient on *SUE_GAAP_Error* (0.033), indicating that the previously identified GAAP earnings surprises with measurement error bias downwards market response to GAAP earnings. The chow test further shows that they are not significantly different. Nevertheless, prior studies using the difference between actual GAAP EPS and forecast non-GAAP EPS to measure GAAP forecast error underestimate investors' attention on GAAP earnings. Compared to the coefficient on SUE_GAAP_Error (0.034) in column (5), the estimated response to GAAP earnings surprise (0.039) is also increased by 14.7% in column (6). Though the magnitude is small, this result provides suggestive evidence on the validity of prior concerns on the measurement error (Heflin and Hsu, 2008; Doyle et al., 2013).

Insert Table 3.4 about here

[17] In untabulated analysis, the chow test is used to test whether the coefficients on *SUE_NonGAAP* and *SUE_GAAP* are significantly different. The chow test statistics is 23.48, and it is significant at 1% level.

To further examine whether the market responds to the measurement error component, I take the difference between the previously identified GAAP earnings surprises with measurement error (*SUE_GAAP_Error*) and the corrected GAAP earnings surprise (*SUE_GAAP*), which captures the forecast exclusions, scaled by stock price, and estimate the following regression:

$$CAR_{[-1,+1]} = \alpha_4 + \beta_{41} SUE\_GAAP + \beta_{42} Diff^{Exclusions} + Controls$$

$$+ Country/year\ fixed\ effect + \varepsilon_4 \qquad (3.7)$$

The forecast exclusions $Diff^{Exclusions}$ is the difference between forecast GAAP EPS and forecast non-GAAP EPS.[18] Table 3.5 presents the regression result of the short-window CAR on corrected GAAP earnings surprises and forecast exclusions. Column (1) and (2) of Table 3.5 present the results from estimating specification (3.7) where the dependent variables are EW_CAR and VW_CAR. The coefficient on $Diff^{Exclusions}$ is 1.6% in column (1), statistically significant at 1% level, and it is 1.1% in column (2) at 10% significance level. These results are inconsistent with hypothesis 3.2 and indicate that the measurement error component (forecast exclusions) provides incrementally useful information in addition to the information found in GAAP forecasts. The forecast exclusions are positively associated with the short-window CAR, indicating that investors react positively when the forecast GAAP EPS is higher than the forecast non-GAAP EPS.

Although the exclusion items are typically claimed to be transitory and less persistent (Gu and Chen, 2004), my results corroborate Whipple's (2015) argument that the exclusion items are informative. Merkley et al. (2013) and Lansford, Lev, and Tucker (2013) provide a possible explanation, namely that the disaggregated forecasts result in an enriched information environment and more credible analysts forecast, which in turn improves investors' understanding of the firm. Even though correcting the measurement error of

[18] The forecast exclusions construct ($Diff^{Exclusions}$) is shown in equation (3.1), (3.2) and (3.3)

GAAP earnings surprise does not result in a different inference on the informativeness of non-GAAP earnings, the results in Table 3.5 show that previously identified investors' preference for non-GAAP earnings is at least partly explained by the measurement error (i.e., forecast exclusions).

Insert Table 3.5 about here

3.5.3 Post earnings announcement drift using different definitions of earnings surprises

Although investors may not assimilate GAAP earnings surprise signals immediately around the date of the earnings announcement, they may assign more weight to them over longer periods following the announcement, resulting in a stock return drift in the direction of earnings surprises. Therefore, to examine the association between long-term cumulative abnormal return and different definitions of earnings surprises, I estimate the following regression: models

$$CAR_{[+2,+64]} = \alpha_5 + \beta_5 SUE\_NonGAAP\_std + Controls + Country/\ year\ fixed\ effect + \varepsilon_5 \quad (3.8)$$

$$CAR_{[+2,+64]} = \alpha_6 + \beta_6 SUE\_GAAP\_std + Controls + Country/year\ fixed\ effect + \varepsilon_6 \quad (3.9)$$

Where $CAR_{[+2,+64]}$ is either cumulative equally weighted abnormal return (*EW_CAR*) or cumulative value weighted abnormal return (*VW_CAR*), cumulated from 2 trading days following the announcement to 64 trading days following the announcement. *Controls* represents a vector of control variables comprising *Size*, *MTB* and *Beta* to capture the effects of firm characteristics on the CAR. Country and year fixed effects are also included in the regression. To reduce the effect of outliers, following previous post earnings announcement drift studies (Bernard and Thomas; 1989, Doyle, Lundholm, and Soliman; 2003 and Narayanamoorthy, 2003), I classify firms into 10 portfolios based on calculated earnings surprise. I subtract 0.5 from the respective SUE decile rank for a zero median. Thus, the coefficient on each independent variable in Equation (5) and (6) can be interpreted as the cumulative abnormal return to a hedge portfolio that takes a long position in the most positive earnings surprise decile rank and a short position in the most negative earnings surprise decile rank.

Table 3.6 presents the regression results of subsequent quarter CAR following the earnings announcement date on standardised earnings surprises. The coefficients on standardised Non-GAAP earnings surprises (*SUE_NonGAAP_std)* are only 1.6% and 1.7% in columns (1) and (3), lower than the coefficients on standardised GAAP earnings surprises (*SUE_GAAP_std*) (2.0% and 1.9% respectively in column (2) and (4).[19] The coefficients are all significant at 1% level, indicating that both current non-GAAP and GAAP earnings surprises are positively associated with subsequent quarter CAR. Nevertheless, the non-GAAP drift is lower than the GAAP drift.

While prior research focuses mainly on the time series Compustat-based drift and I/B/E/S-based non-GAAP drift (e.g. Doyle, Lundholm, and Soliman, 2003; Livnat and Mendenhall, 2006), using the corrected measure of GAAP earnings surprises, my results reject hypothesis 3.3 and indicates the superiority of the GAAP based earnings surprise relative to the non-GAAP earnings surprise in understanding the drift. As GAAP earnings contain exclusion items, this result provides additional evidence to support Doyle, Lundholm and Soliman's (2003) finding that market delayed responding to information implicit in exclusion items.

Insert Table 3.6 about here

[19] In untabulated analysis, the chow test is used to test whether the coefficients on *SUE_NonGAAP_std* and *SUE_GAAP_std* are significantly different. The chow test statistics for column (1) and (2) is 3.25, and it is significant at 10% level. The chow test statistics for column (3) and (4) is 1.03, and it is insignificant.

3.5.4 The effect of GAAP loss on market reactions to different earnings surprise measures

Using more precisely measured GAAP earnings surprises, I further assess the relative informativeness and PEAD of GAAP and non-GAAP earnings in a unique setting where firms report negative actual GAAP EPS. This is to assess the possibility that investors perceive non-GAAP earnings to be particularly opportunistic and react less to the corresponding earnings surprises when firms report a GAAP loss. Because analysts are more likely to inflate non-GAAP forecasts for loss-making firms considering their incentives to curry favour with managers (McNichols and O`Brien, 1997) to attract investment banking business (Lin and McNichols, 1998). The whole sample is split into two groups— profit firms with positive or zero I/B/E/S actual GAAP EPS and loss firms with negative I/B/E/S actual GAAP EPS. I further estimate models (1), (2), (5) and (6) respectively for profit and loss firms.

The two-way sort of decile rank on earnings surprises and profit/loss firms can be sensitive to different orders of sorting. Specifically, independent sorting means ranking on earnings surprises prior to differentiate profit and loss firms, while conditional sorting refers to ranking firms into 10 portfolios within each group of profit firms and loss firms. To see whether the sample distribution differs for the above two sorting methods, Table 3.7 presents the number of firm-year observations by portfolio ranks and profit/loss firms. The results show that the sample is not homogeneously distributed between portfolios 1 and 10. In particular, for loss firms, most observations are concentrated on portfolios 1 and 2 for both portfolios ranked by *SUE_NonGAAP* (35% and 16%) and portfolios ranked by *SUE_GAAP* (39% and 19%). This indicates that analysts may be more optimistic for loss firms, resulting in relatively large negative earnings surprises. Alternatively, as loss firms are usually associated with higher uncertainty compared to profit firms (e.g. Konstantinidi and Pope, 2016), analysts may find it more difficult to forecast future performance of loss firms. Thus, the distribution between portfolio 1 to 10 for loss firms are less even and mainly focused on portfolios 1, 2 and 10.

Insert Table 3.7 about here

Table 3.8 presents different market reactions to GAAP and non-GAAP earnings surprises for profit and loss firms. The earnings response coefficients (ERCs) on *SUE_NonGAAP* in columns (1) and (2) of Panel A are 18.2% and 2.7% respectively, indicating the market reaction to non-GAAP earnings is much stronger for profit-firms than loss firms. Similarly, the ERCs on *SUE_GAAP* is lower for loss firms (2.1%) in column (4) compared to profit firms (7.9%) in column (3). The same inferences can be drawn using *vw_car*. Leung and Veenman (2018) compare the market reactions to non-GAAP earnings and GAAP earnings only for loss firms, especially when firms convert a GAAP loss into a non-GAAP profit by excluding recurring expenses. My results directly compare the relative informativeness of non-GAAP and GAAP earnings for both profit and loss firms.

In contrast to the argument that investors value non-GAAP earnings more for incremental information when firms report a GAAP loss (Leung and Veenman, 2018), my findings show that the ERCs on non-GAAP earnings (2.7%) do not differ substantially from ERCs on GAAP earnings (2.1%) for loss firms. This could be a result of investors' perceptions and reactions to potential aggressive and opportunistic non-GAAP reporting (Kolev, Marquardt, and McVay, 2008; Barth, Beaver, and Landsman, 2012).[20]

The results of Panel B and Panel C show that non-GAAP based drift does not exist for loss firms as the coefficients on *SUE_NonGAAP_std* in column (2) and (6) are statistically insignificant, regardless of independent sorting or conditional sorting. However, there are inconclusive results with regards to GAAP based drift. While the coefficients on

[20] Leung and Veenman (2018) compare firms which report both GAAP loss and non-GAAP earnings figures to those reporting only a GAAP loss. I directly compare market reactions to non-GAAP earnings surprises for profit-making and loss-making firms.

SUE_GAAP_std are significantly negative in column (4) and (8) of Panel B using independent sorting, this does not stand using conditional sorting in Panel C.

Insert Table 3.8 about here

3.5.5 The effect of exclusion items on reactions to different measures of earnings surprise

In this section, I examine the effect of exclusion items on market reactions to GAAP and non-GAAP earnings surprises. As analysts may have incentives to inflate non-GAAP earnings by excluding income-decreasing items (Baik et al., 2009), whether markets are misled by potential analysts' opportunistic non-GAAP adjustments become an important question and a concern of regulators. Thus, I investigate whether market reacts differently to two measures of earnings surprises for different exclusion items in both short-term and long-term. Specifically, I sort and categorise the whole sample into three groups based on the sign of exclusion items. Exclusion items here are defined as the difference between I/B/E/S reported actual GAAP EPS and I/B/E/S reported actual non-GAAP EPS.[21] Thus, positive exclusion items would indicate an actual GAAP EPS higher than the actual non-GAAP EPS, while negative exclusion items represent excluded expenses in the definition of non-GAAP earnings. I then estimate equation (3.1) and (2) respectively within each group to compare earnings response coefficients (ERCs), and I estimate equation (3.5) and (3.6) within each group to compare the magnitude of drift for GAAP and non-GAAP earnings surprises.

Table 3.9 first presents the number of firm-year observations by portfolio ranking and groups of exclusion items for independent sorting. Independent sorting here refers to ranking on earnings surprises prior to ranking on exclusion items. Although the number of observations of portfolio 10 (152) in column (1) is slightly lower than that of portfolio 1

[21] Note that this definition is different from Doyle, Lundholm and Soliman's (2002) measure where Total Exclusions = Pro Forma Earnings – GAAP Earnings. They find a significantly negative coefficient on other exclusions items a the regression of one-year future returns on decile-ranked exclusion items.

(193) for *SUE_NonGAAP*, the proportion of *SUE* rank does not change much across groups of exclusion items for non-GAAP earnings surprises. In contrast, the number of observations of portfolio 10 (599) in column (4) is almost 8 times more than that of portfolio 1 (78) for *SUE_GAAP*, and the number of observations gradually declines from 1,131 of portfolio 1 to 242 of portfolio 10 in column (6). As GAAP earnings surprise can be decomposed into non-GAAP earnings surprises and Exclusion surprises, this indicates that groups with positive actual exclusion items will have more positive exclusion surprises than the other, while groups with negative actual exclusion items will have more negative exclusion surprises than the other. This is not surprising as most exclusion items are deemed to be 'transitory items', which are not expected to recur in the following periods. Thus, analysts tend to report forecast exclusion items as zero.[22]

Insert Table 3.9 about here

Table 3.10 presents the results of regressing short-term and long-term CAR on different earnings surprises by groups of exclusion items. The coefficients on *SUE_NonGAAP* in Panel A of Table 3.10 are 8.4%, 6.8% and 6.3%, respectively in column (1), (3) and (5), indicating that market reacts most strongly to non-GAAP earnings when actual GAAP EPS is larger than actual non-GAAP EPS at the earnings announcement. The coefficients on *SUE_GAAP* are 3.1%, 3.9% and 3.3% respectively in columns (2), (4) and (6), indicating that the market finds GAAP earnings to be most informative when exclusion items are equal to zero. By using an alternative measure of market reaction (cumulative value-weighted abnormal return), the estimates in column (7) to column (12) further support the above inferences. Prior studies show that certain analysts' decisions to exclude selected items are potentially due to self-interest instead of benefiting investors (Lambert, 2004;

[22] Larocque et al. (2018) report that the 25th percentile, median and 75th percentile of exclusions forecast are zero.

Bratten et al., 2020). My results suggest that the market preference to non-GAAP earnings at the earnings announcement are subject to the consideration of possible opportunism behaviours. Specifically, GAAP earnings may play a disciplinary role and market appreciates non-GAAP earnings most when actual GAAP EPS is larger than the non-GAAP EPS.

Panel B and Panel C of Table 3.10 present the results of post earnings announcement drift levels for subsample of exclusion groups using independent sorting and conditional sorting respectively. Independent sorting refers to ranking on earnings surprises prior to ranking on exclusion items, while conditional sorting refers to ranking firms into 10 portfolios within each group of exclusion items. As panel B shows, the non-GAAP based drift only exists when the exclusion items equal to zero, and the magnitude of the drift is smaller than the GAAP based drift— 2% versus 2.9%. The coefficients on *SUE_GAAP_std* are all significant in column (2), (4), (6), (8), (10) and (12), indicating that the GAAP based drift exist for all exclusion groups and investors misprice GAAP earnings on average. The magnitude of GAAP-based drift is the lowest when firms have negative exclusions items, 1.7% compared to 2.9% when exclusions items equal to zero. The results of panel C is slightly different when adopting conditional sorting. Specifically, non-GAAP based drift now exists when firms have income-increasing exclusion items. The coefficients on *SUE_NonGAAP_std*, however, are still insignificant in column (5) and (11), indicating that investors do not misprice non-GAAP earnings when analysts exclude income-decreasing exclusion items. Though there is inconclusive result with regards to non-GAAP based drift, according to Whipple (2015), whether investors misprice non-GAAP exclusions are subject to the persistence of exclusion items. Specifically, the information on more persistent exclusion items are not fully utilised at the earnings announcement date.

Insert Table 3.10 about here

3.6 Conclusion

This study examines the market reactions to various definitions of earnings surprises (GAAP earnings surprises, non-GAAP earnings surprises and GAAP earnings surprises with measurement error) in both short-term and long-term. Due to the unavailability of GAAP forecasts data before 2004, prior studies on the informativeness of different earnings definitions and PEAD calculate GAAP earnings surprise using the difference between GAAP actuals and non-GAAP forecasts. This measurement error problem is identified as a major limitation that may potentially contaminate existing results (Lambert, 2004; Cohen et al., 2007). This paper overcomes the issue by measuring GAAP earnings surprises as the difference between GAAP actuals and GAAP forecasts from I/B/E/S. In addition, I select an international sample consisting of firms from the UK and 10 Eurozone countries and contribute beyond prior studies using US sample. I first compare investors' preference for different earnings measures at the earnings announcement date. I then explore the post earnings announcement abnormal returns in long-term period using different definitions of earnings surprises. As prior studies have examined the magnitude and patterns of PEAD using analysts' non-GAAP forecast errors, time series model and Compustat earnings surprises (Doyle, Lundholm and Soliman, 2003; Livnat and Mendenhall, 2006), the pattern and magnitude of PEAD for GAAP based earnings surprise and its comparison to non-GAAP based drift remains an interesting question.

My investigation of three-day window abnormal returns around earnings announcement date after correcting for the prior measurement error is consistent with the argument that investors perceive non-GAAP earnings to be more informative than GAAP earnings. However, previously identified GAAP earnings surprises with measurement error downwardly bias market responses to GAAP earnings. My findings further reveal that the market responds positively to the measurement error component, indicating that forecast exclusions provides incremental useful information in addition to the information captured in GAAP forecasts. Collectively, evidence suggests that previously identified investors' preference for non-GAAP earnings is at least partly explained by the measurement error component (forecast exclusions). When separating the sample into profit-making and loss-making firms, I find that the short-term market reaction to non-GAAP earnings is more pronounced for profit-making firms compared to loss-making firms. This result supports the view that capital market does not seem to be entirely misled by possible manipulation of earnings adjustments and non-GAAP earnings, because analysts are more likely to inflate non-GAAP forecasts when firms are likely to report a GAAP loss for self-interest and economic incentives.

In addition to the short-term market reactions, I find that the GAAP-based PEAD after correcting the measurement error is higher than the non-GAAP based PEAD, indicating that investors may not utilise the information captured by GAAP earnings efficiently compared to that of non-GAAP earnings. This is consistent with the view that market may place less weight on vague and uncertain information contained in exclusion items shortly after earnings announcement date. In the longer term, as the information environment is enriched and investors digest information from various sources, investors may place extra weight on the more regulated GAAP earnings metrics.

Overall, my findings provide insight into both short-term and long-term market reactions to analysts' GAAP and non-GAAP earnings surprises in an international setting. It also provides additional evidence on the effect of measurement error on prior findings of investors' preference for GAAP and non-GAAP earnings. This paper is of relevance to the understanding the true nature of the PEAD anomaly and finding the most effective form of earnings surprises in explaining the PEAD. Future research can investigate market reactions to alternative definitions of earnings surprises such as one defined by the difference between managers reported pro forma earnings and analysts' non-GAAP forecasts. In addition, although this paper considers the effect of firm size, market to book ratio and market beta, future research could further analyse the conditional effect of firm characteristics on the relative informativeness between non-GAAP and GAAP earnings metrics. Such characteristics may include leverage, liquidity etc.

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Tables of Chapter 3

Table 3.1 Number of firm observations by financial year and country

	Country												
Year	Austria	Belgium	Finland	France	German	Greece	Ireland	Italy	Netherlands	Portugal	Spain	United Kingdom	Total
2004	11	35	28	150	137	39	11	93	36	20	33	57	650
2005	20	47	77	230	198	43	30	125	66	25	65	223	1149
2006	30	55	76	277	237	48	30	139	71	22	69	250	1304
2007	41	62	77	291	285	46	35	153	78	25	80	271	1444
2008	42	66	80	306	289	47	34	143	78	31	85	295	1496
2009	40	58	77	274	264	41	30	128	75	29	84	325	1425
2010	33	63	76	276	251	33	28	150	72	28	87	331	1428
2011	35	62	90	276	239	26	26	140	72	28	83	354	1431
2012	34	51	69	276	222	23	23	123	67	25	81	341	1335
2013	32	51	76	247	251	22	21	131	65	28	71	372	1367
2014	34	52	79	265	286	22	25	117	65	25	69	375	1414
2015	35	51	83	294	304	25	24	145	64	22	71	396	1514
2016	35	49	90	314	308	24	23	140	67	20	74	420	1564
2017	34	49	87	318	307	24	23	152	66	23	76	455	1614
2018	20	32	90	127	143	4	16	45	44	8	74	321	924
Total	476	783	1155	3921	3721	467	379	1924	986	359	1102	4786	20059

This table presents the number of firm observations by financial year and country. The full sample consists of 2,757 firms from 12 countries. The sample period is Jan 2004 through December 2018.

Table 3.2 Descriptive statistics

Stats	N	Mean	S.D.	Min	Max	P25	Median	P75
SUE_GAAP	20059	-0.030	0.141	-1.063	0.172	-0.014	-0.001	0.005
SUE_NonGAAP	20059	-0.012	0.072	-0.512	0.133	-0.006	0.000	0.005
SUE_GAAP_Error	20059	-0.036	0.155	-1.146	0.200	-0.021	-0.002	0.004
EW_CAR	20059	0.008	0.058	-0.169	0.192	-0.022	0.005	0.036
EW_PEAD	19492	0.036	0.174	-0.480	0.633	-0.056	0.033	0.124
VW_CAR	19369	0.008	0.057	-0.167	0.189	-0.022	0.005	0.036
VW_PEAD	18130	0.036	0.173	-0.469	0.629	-0.056	0.033	0.124
Size	20059	6.353	2.064	2.163	11.146	4.784	6.230	7.809
MTB	20059	2.483	2.633	-1.856	16.842	1.037	1.724	2.952
Beta	20059	0.648	0.484	-0.353	2.067	0.285	0.611	0.959

This table presents the descriptive statistics with winsorisation. Extreme values are replaced with 1st and 99th percentile values. *SUE_GAAP* is the earnings surprise calculated using I/B/E/S actual GAAP EPS and I/B/E/S forecast GAAP EPS, scaled by the stock price no more than 30 days prior to the earnings announcement date. *SUE_NonGAAP* is the earnings surprise calculated using I/B/E/S actual Non-GAAP EPS and I/B/E/S forecast Non-GAAP EPS, scaled by the stock price no more than 30 days prior to the earnings announcement date. *SUE_GAAP_Error* is the earnings surprise calculated using I/B/E/S actual GAAP EPS and I/B/E/S forecast Non-GAAP EPS, scaled by the stock price no more than 30 days prior to the earnings announcement date. *EW_CAR* is the equally weighted cumulative abnormal return for the three-day window [-1,1] centred on the earnings announcement date. *EW_PEAD* is the equally weighted abnormal return on a stock, cumulated from 2 trading days following the announcement to 64 trading days following the announcement. *VW_CAR* is the value-weighted cumulative abnormal return for the three-day window [-1,1] centred on the earnings announcement date. *VW_PEAD* is the value-weighted abnormal return on a stock, cumulated from 2 trading days following the announcement to 64 trading days following the announcement. *Size* is the natural logarithm of market value in millions of Euros at the end of the fiscal year. Market value is the share price multiplied by the number of ordinary shares in issue. *MTB* is the ratio of market capitalisation to book value of shareholders' equity at the end of the fiscal year. *Beta* is the estimated coefficient on the market index return in a CAPM model regression for firms with daily returns in the 90 trading days before the earnings announcement date. All variable definitions are presented in Appendix A3.1.

Table 3.3 Univariate analysis of country-level short-window cumulative abnormal returns (CAR) and of subsequent quarter CAR

	(1)	(2)	(3)	(4)
	EW_CAR	*EW_PEAD*	*VW_CAR*	*VW_PEAD*
Austria	0.0065***	0.0309***	0.0059***	0.0298***
Belgium	0.0023	0.0443***	0.0024	0.0399***
Finland	0.0006	0.0605***	0.0006	0.0577***
France	0.0090***	0.0322***	0.0088***	0.0307***
Germany	0.0064***	0.0349***	0.0066***	0.0356***
Greece	-0.0012	0.0402***	-0.0012	0.0421***
Ireland	0.0208***	0.0238*	0.019***	0.025**
Italy	0.0105***	0.0193***	0.010***	0.023***
Netherlands	0.0037	0.0520***	0.0029	0.055***
Portugal	0.0055**	0.0285***	0.0057***	0.0287***
Spain	-0.0047***	0.0139**	-0.0049***	0.0162***
United Kingdom	0.0133***	0.0300***	0.0133***	0.0315***

This table presents a country level short-window CAR and subsequent quarter CAR regression. *EW_CAR* is the equally weighted cumulative abnormal return for the three-day window [-1,1] centred on the earnings announcement date. *EW_PEAD* is the equally weighted abnormal return on a stock, cumulated from 2 trading days following the announcement to 64 trading days following the announcement. *VW_CAR* is the value-weighted cumulative abnormal return for the three-day window [-1,1] centred on the earnings announcement date. *VW_PEAD* is the value-weighted abnormal return on a stock, cumulated from 2 trading days following the announcement to 64 trading days following the announcement. All variable definitions are presented in Appendix A3.1. *, **, *** indicate significance levels (two-sided) of 10%, 5% and 1%, respectively.

Table 3.4 Regression of short-window CAR on different measurement of earnings surprises

	(1)	(2)	(3)	(4)	(5)	(6)
VARIABLES	*EW_CAR*	*EW_CAR*	*EW_CAR*	*VW_CAR*	*VW_CAR*	*VW_CAR*
SUE_NonGAAP	0.067***			0.070***		
	(11.76)			(10.90)		
SUE_GAAP		0.036***			0.039***	
		(12.09)			(12.53)	
SUE_GAAP_Error			0.033***			0.034***
			(12.03)			(11.99)
Size	-0.000	-0.000	-0.000	-0.000*	-0.000*	-0.000*
	(-1.51)	(-1.52)	(-1.57)	-(1.74)	-(1.80)	-(1.78)
MTB	-0.001**	-0.000***	-0.000***	-0.000**	-0.000***	-0.001***
	(-2.52)	(-2.94)	(-2.99)	-(2.40)	-(2.84)	-(2.88)
Beta	-0.001	-0.001	-0.001	-0.002	-0.001	-0.001
	(-1.52)	(-1.13)	(-0.99)	-(1.58)	-(1.14)	-(1.05)
Constant	0.008**	0.007**	0.007**	0.007*	0.007*	0.007*
	(2.05)	(1.96)	(1.99)	(1.90)	(1.80)	(1.83)
Chow test *SUE_GAAP*= *SUE_GAAP_Error*		0.77			1.58	
Country FE	Y	Y	Y	Y	Y	Y
Year FE	Y	Y	Y	Y	Y	Y
Observations	20059	20059	20059	19369	19369	19369
R-squared	0.018	0.018	0.018	0.018	0.019	0.019

This table presents regression result of short-window CAR on different measurement of earnings surprises. *EW_CAR* is the equally weighted cumulative abnormal return for the three-day window [-1,1] centred on the earnings announcement date. *VW_CAR* is the value-weighted cumulative abnormal return for the three-day window [-1,1] centred on the earnings announcement date. *SUE_NonGAAP* is the earnings surprise calculated using I/B/E/S actual Non-GAAP EPS and I/B/E/S forecast Non-GAAP EPS, scaled by the stock price no more than 30 days prior to the earnings announcement date. *SUE_GAAP* is the earnings surprise calculated using I/B/E/S actual GAAP EPS and I/B/E/S forecast GAAP EPS, scaled by the stock price no more than 30 days prior to the earnings announcement date. *SUE_GAAP_Error* is the earnings surprise calculated using I/B/E/S actual GAAP EPS and I/B/E/S forecast Non-GAAP EPS, scaled by the stock price no more than 30 days prior to the earnings announcement date. All continuous variables are winsorised at the top and bottom 1% of each distribution. t-statistics are reported in parentheses. *, **, *** indicate significance levels (two-sided) of 10%, 5% and 1%, respectively.

Table 3.5 Regression of short-window CAR on GAAP earnings surprises and forecast exclusions

	(1)	(2)
VARIABLES	*EW_CAR*	*VW_CAR*
SUE_GAAP	0.036***	0.039***
	(12.17)	(12.56)
$Diff^{Exclusions}$	0.016***	0.011*
	(2.65)	(1.69)
Size	-0.000*	-0.000*
	(-1.66)	(-1.89)
MTB	-0.000***	-0.000***
	(-3.00)	(-2.88)
Beta	-0.001	-0.001
	(-0.98)	(-1.04)
Constant	0.007**	0.007*
	(2.01)	(1.84)
Country FE	Y	Y
Year FE	Y	Y
Observations	20059	19369
R-squared	0.018	0.019

This table presents regression result of the short-window CAR on GAAP earnings surprises and forecast exclusions. $Diff^{Exclusions}$ is the difference between the previously identified GAAP earnings surprises with measurement error (*SUE_GAAP_Error*) and the corrected GAAP earnings surprise (*SUE_GAAP*), identified as the forecast exclusions. *EW_CAR* is the equally weighted cumulative abnormal return for the three-day window [-1,1] centred on the earnings announcement date. *VW_CAR* is the value-weighted cumulative abnormal return for the three-day window [-1,1] centred on the earnings announcement date. All variable definitions are presented in Appendix A3.1. All continuous variables are winsorised at the top and bottom 1% of each distribution. t-statistics are reported in parentheses. *, **, *** indicate significance levels (two-sided) of 10%, 5% and 1%, respectively.

Table 3.6 Regression of subsequent quarter CAR on different measurement of standardised earnings surprises

	(1)	(2)	(3)	(4)
VARIABLES	*EW_PEAD*	*EW_PEAD*	*VW_PEAD*	*VW_PEAD*
SUE_NonGAAP_std	0.016***		0.017***	
	(4.38)		(4.39)	
SUE_GAAP_std		0.020***		0.019***
		(5.31)		(4.99)
Size	0.004***	0.004***	0.003***	0.003***
	(6.16)	(6.08)	(4.77)	(4.74)
MTB	-0.001**	-0.001***	-0.001***	-0.002***
	(-2.47)	(-2.74)	(-3.09)	(-3.35)
Beta	-0.005*	-0.004	-0.005**	-0.005
	(-1.80)	(-1.59)	(-1.83)	(-1.65)
Constant	0.037***	0.037***	0.042***	0.042***
	(3.46)	(3.50)	(3.90)	(3.92)
Country. FE	Y	Y	Y	Y
Year. FE	Y	Y	Y	Y
Observations	19492	19492	18130	18130
R-squared	0.123	0.123	0.134	0.134

This table presents the regression result of subsequent quarter CAR following the earnings announcement date on standardised earnings surprises. *EW_PEAD* is the equally weighted abnormal return on a stock, cumulated from 2 trading days following the announcement to 64 trading days following the announcement. *VW_PEAD* is the value-weighted abnormal return on a stock, cumulated from 2 trading days following the announcement to 64 trading days following the announcement. Firms are ranked and classified into 10 portfolios for each country-year according to the earnings surprise *SUE_NonGAAP*, *SUE_GAAP and SUE_GAAP_Error*. *SUE_NonGAAP_std, SUE_GAAP_std and SUE_GAAP_Error_std* are standardised to the range [0, 1], and are futher subtracted by 0.5 for a median of 0. Other variables expect for the standardised earnings surprises are winsorised at the top and bottom 1% of each distribution. All variable definitions are presented in Appendix A3.1. t-statistics are reported in parentheses *, **, *** indicate significance levels (two-sided) of 10%, 5% and 1%, respectively.

Table 3.7 Number of firm-year observations by portfolio ranks and GAAP EPS loss

Portfolios ranked by *SUE_NonGAAP*	Number of observations		Portfolios ranked by *SUE_GAAP*	Number of observations	
	Loss=0	*Loss*=1		*Loss*=0	*Loss*=1
Portfolio 1	672	1,363	Portfolio 1	521	1,513
Portfolio 2	1,312	626	Portfolio 2	1,186	749
Portfolio 3	1,663	316	Portfolio 3	1,573	387
Portfolio 4	1,835	182	Portfolio 4	1,806	216
Portfolio 5	1,809	134	Portfolio 5	1,817	116
Portfolio 6	1,771	118	Portfolio 6	1,845	132
Portfolio 7	1,796	127	Portfolio 7	1,787	80
Portfolio 8	1,768	164	Portfolio 8	1,815	114
Portfolio 9	1,670	293	Portfolio 9	1,761	201
Portfolio 10	1,326	547	Portfolio 10	1,511	362
Total	15622	3870	Total	15622	3870

This table presents the number of firm-year observations by portfolio ranks and actual GAAP EPS loss. *Loss* is a dummy variable that takes the value of 1 if I/B/E/S actual GAAP EPS is negative, and otherwise 0. Firms are ranked and classified into 10 portfolios for each country-year according to the earnings surprise *SUE_NonGAAP* and *SUE_GAAP*. *SUE_NonGAAP* is the earnings surprise calculated using I/B/E/S actual Non-GAAP EPS and I/B/E/S forecast Non-GAAP EPS, scaled by the stock price no more than 30 days prior to the earnings announcement date. *SUE_GAAP* is the earnings surprise calculated using I/B/E/S actual GAAP EPS and I/B/E/S forecast GAAP EPS, scaled by the stock price no more than 30 days prior to the earnings announcement date.

Table 3.8 Market reactions to GAAP and non-GAAP earnings surprises for loss firms

Panel A Regression of short-window CAR on different earnings surprises for profit and loss firms

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
	EW_CAR				*VW_CAR*			
VARIABLES	Profit firms	Loss firms	Profit firms	Loss firms	Profit firms	Loss firms	Profit firms	Loss firms
SUE_NonGAAP	0.182***	0.027***			0.174***	0.029***		
	(12.08)	(3.23)			(11.18)	(3.42)		
SUE_GAAP			0.079***	0.021***			0.077***	0.024***
			(7.74)	(4.89)			(7.26)	(5.31)
Size	-0.002***	0.001	-0.002***	0.001	-0.002***	0.001	-0.002***	0.001
	(-7.12)	(1.30)	(-7.1)	(1.38)	(-7.48)	(1.38)	(-7.44)	(1.48)
MTB	0.000	-0.001**	0.000	-0.001***	0.000	-0.001**	0.000	-0.001***
	(0.34)	(-2.48)	(0.2)	(-2.87)	(0.5)	(-2.49)	(0.37)	(-2.92)
Beta	0.000	0.000	0.000	0.001	0.000	0.001	0.000	0.001
	(0.37)	(0.00)	(0.37)	(0.32)	(0.19)	(0.24)	(0.15)	(0.58)
Constant	0.012***	0.009	0.012***	0.008	0.013***	0.003	0.013***	0.002
	(3.05)	(0.79)	(3.18)	(0.74)	(3.29)	(0.27)	(3.39)	(0.19)
Country FE	Y	Y	Y	Y	Y	Y	Y	Y
Year FE	Y	Y	Y	Y	Y	Y	Y	Y
Observations	16113	3946	16113	3946	15616	3753	15616	3753
R-squared	0.026	0.014	0.021	0.018	0.026	0.014	0.022	0.018

Table 3.8 (continued)

Panel B Regression of subsequent quarter CAR on different measurement of standardised earnings surprises for profit and loss firms (Independent sorting)

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
	EW_CAR				*VW_CAR*			
VARIABLES	Profit firms	Loss firms	Profit firms	Loss firms	Profit firms	Loss firms	Profit firms	Loss firms
SUE_NonGAAP_std	0.013***	-0.009			0.016***	-0.013		
	(3.32)	-(.94)			(3.93)	-(1.38)		
SUE_GAAP_std			0.016***	-0.020*			0.016***	-0.022**
			(3.95)	-(1.92)			(3.83)	-(2.02)
Size	0.001	0.005**	0.001	0.005**	0.000	0.004*	0.000	0.003
	(0.84)	(2.36)	(0.86)	(2.13)	(0.07)	(1.78)	(0.11)	(1.46)
MTB	0.000	-0.002**	0.000	-0.002*	-0.001	-0.003**	-0.001	-0.002**
	(-0.62)	(-1.99)	(-0.71)	(-1.73)	(-1.04)	(-2.26)	-(1.16)	(-1.99)
Beta	0.001	-0.001	0.001	-0.001	-0.003	0.006	-0.003	0.006
	(0.24)	(-0.17)	(0.29)	(-0.17)	(-0.9)	(0.88)	(-0.86)	(0.88)
Constant	0.041***	0.085**	0.041***	0.084**	0.047***	0.084**	0.047***	0.085**
	(3.96)	(2.36)	(3.97)	(2.36)	(4.49)	(2.29)	(4.49)	(2.34)
Country FE	Y	Y	Y	Y	Y	Y	Y	Y
Year FE	Y	Y	Y	Y	Y	Y	Y	Y
Observations	15623	3870	15623	3870	14503	3628	14503	3628
R-squared	0.125	0.135	0.126	0.135	0.14	0.141	0.14	0.142

Table 3.8 (continued)

Panel C Regression of subsequent quarter CAR on different measurement of standardised earnings surprises for profit and loss firms (Conditional sorting)

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
	EW_CAR				*VW_CAR*			
VARIABLES	Profit firms	Loss firms	Profit firms	Loss firms	Profit firms	Loss firms	Profit firms	Loss firms
SUE_NonGAAP_std	0.013***	-0.003			0.014***	-0.013		
	(3.52)	(-0.26)			(3.86)	-(1.12)		
SUE_GAAP_std			0.016***	-0.014			0.016***	-0.021
			(4.42)	(-1.26)			(4.28)	-(1.58)
Size	0.001	0.005**	0.001	0.005**	0.000	0.004*	0.000	0.004
	(0.86)	(2.27)	(0.90)	(2.27)	(0.09)	(1.78)	(0.14)	(1.62)
MTB	0.000	-0.002**	0.000	-0.002*	-0.001	-0.003**	-0.001	-0.002*
	(-0.61)	(-1.99)	(-0.68)	(-1.76)	(-1.03)	(-2.23)	(-1.13)	-(1.95)
Beta	0.001	-0.001	0.001	-0.001	-0.003	0.006	-0.003	0.006
	(0.23)	-(0.17)	(0.29)	(-0.21)	(-0.91)	(0.85)	(-0.87)	(0.82)
Constant	0.042***	0.088**	0.041***	0.087**	0.048***	0.086**	0.047***	0.087**
	(4.00)	(2.44)	(3.99)	(2.42)	(4.53)	(2.34)	(4.51)	(2.38)
Country FE	Y	Y	Y	Y	Y	Y	Y	Y
Year FE	Y	Y	Y	Y	Y	Y	Y	Y
Observations	15623	3870	15623	3870	14503	3628	14503	3628
R-squared	0.125	0.135	0.126	0.135	0.14	0.141	0.14	0.142

This table presents different market reactions to GAAP and non-GAAP earnings surprises for profit and loss firms. Panel A presents the regression result of short-window CAR on different measurement of earnings surprises for profit and loss firms separately. Panel B presents the regression result of subsequent quarter CAR on different measurement of standardised earnings surprises for profit and loss firms using independent sorting. Panel C presents the regression result of subsequent quarter CAR on different measurement of standardised earnings surprises for profit and loss firms using conditional sorting. Firms with negative actual GAAP EPS are classified as loss firms, otherwise are profit firms. *EW_CAR* is the equally weighted cumulative abnormal return for the three-day window [-1,1] centred on the earnings announcement date. *EW_PEAD* is the equally weighted abnormal return on a stock, cumulated from 2 trading days following the announcement to 64 trading days following the announcement. *SUE_NonGAAP* is the earnings surprise calculated using I/B/E/S actual Non-GAAP EPS and I/B/E/S forecast Non-GAAP EPS, scaled by the stock price no more than 30 days prior to the earnings announcement date. *SUE_GAAP* is the earnings surprise calculated using I/B/E/S actual GAAP EPS and I/B/E/S forecast GAAP EPS, scaled by the stock price no more than 30 days prior to the earnings announcement date. Firms are further classified into 10 portfolios for each country year according to the earnings surprise *SUE_NonGAAP and SUE_GAAP*. *SUE_NonGAAP_std and SUE_GAAP_std* are standardised to the range [0, 1], and are futher subtracted by 0.5 for a median of 0. All continuous variables are winsorised at the top and bottom 1% of each distribution. All variable definitions are presented in Appendix A3.1. t-statistics are reported in parentheses. *, **, *** indicate significance levels (two-sided) of 10%, 5% and 1%, respectively.

Table 3.9 Number of firm-year observations by exclusion groups and portfolio ranks

	Number of observations				Number of observations		
Portfolios ranked by *SUE_NonGAAP*	(1) Positive exclusion items actual GAAP EPS > actual Non-GAAP EPS	(2) Zero exclusion items actual GAAP EPS = actual Non-GAAP EPS	(3) Negative exclusion items actual GAAP EPS < actual Non-GAAP EPS	Portfolios ranked by *SUE_GAAP*	(4) Positive exclusion items actual GAAP EPS > actual Non-GAAP EPS	(5) Zero exclusion items actual GAAP EPS = actual Non-GAAP EPS	(6) Negative exclusion items actual GAAP EPS < actual Non-GAAP EPS
Portfolio 1	193	1,347	551	Portfolio 1	78	881	1,131
Portfolio 2	217	1,245	532	Portfolio 2	105	925	961
Portfolio 3	236	1,229	568	Portfolio 3	102	1,029	887
Portfolio 4	262	1,176	642	Portfolio 4	94	1,198	790
Portfolio 5	210	1,182	607	Portfolio 5	99	1,214	675
Portfolio 6	223	1,051	669	Portfolio 6	138	1,370	524
Portfolio 7	213	1,085	681	Portfolio 7	183	1,322	418
Portfolio 8	178	1,081	733	Portfolio 8	292	1,310	386
Portfolio 9	186	1,130	701	Portfolio 9	380	1,296	340
Portfolio 10	152	1,109	670	Portfolio 10	599	1,090	242
Total	2070	11635	6354	Total	2070	11635	6354

This table presents the number of firm-year observations by exclusion groups and portfolio ranks. Firms are first ranked and classified into 10 portfolios for each country-year according to the earnings surprise *SUE_NonGAAP* and *SUE_GAAP*. *SUE_NonGAAP* is the earnings surprise calculated using I/B/E/S actual Non-GAAP EPS and I/B/E/S forecast Non-GAAP EPS, scaled by the stock price no more than 30 days prior to the earnings announcement date. *SUE_GAAP* is the earnings surprise calculated using I/B/E/S actual GAAP EPS and I/B/E/S forecast GAAP EPS, scaled by the stock price no more than 30 days prior to the earnings announcement date. The whole sample is then classified into three groups according to whether the exclusion items is positive, zero or negative. Exclusion items is the difference between actual GAAP EPS and actual Non-GAAP EPS.

Table 3.10 Market reaction to GAAP and non-GAAP earnings surprises by different exclusion groups

Panel A Regression of short-window CAR on different earnings surprises by different exclusion groups

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)
	EW_CAR						*VW_CAR*					
	Positive exclusion items actual GAAP EPS > actual Non-GAAP EPS		Zero exclusion items actual GAAP EPS = actual Non-GAAP EPS		Negative exclusion items actual GAAP EPS < actual Non-GAAP EPS		Positive exclusion items actual GAAP EPS > actual Non-GAAP EPS		Zero exclusion items actual GAAP EPS = actual Non-GAAP EPS		Negative exclusion items actual GAAP EPS < actual Non-GAAP EPS	
VARIABLES												
SUE_NonGAAP	0.084***		0.068***		0.063***		0.079***		0.074***		0.066***	
	(4.03)		(9.86)		(5.39)		(3.69)		(10.18)		(5.41)	
SUE_GAAP		0.031**		0.039***		0.033***		0.035**		0.048***		0.039***
		(2.36)		(8.29)		(7.3)		(2.46)		(8.94)		(7.78)
Size	-0.002**	-0.001*	-0.000	-0.000	-0.000	-0.001	-0.002**	-0.001*	-0.000	-0.000	-0.000	-0.001*
	(-2.3)	(-1.73)	(-0.63)	(-0.15)	(-0.25)	(-1.37)	(-2.41)	(-1.88)	(-0.74)	(-0.29)	(-0.51)	(-1.73)
MTB	-0.000	-0.000	-0.001***	-0.001***	0.000	0.000	-0.000	-0.000	-0.001***	-0.001***	0.000	0.000
	(-0.41)	(-0.27)	(-4.34)	(-4.32)	(1.12)	(0.66)	(-0.37)	(-0.2)	(-4.19)	(-4.18)	(1.18)	(0.64)
Beta	-0.002	-0.003	-0.002	-0.002*	0.000	0.002	-0.002	-0.003	-0.002	-0.002*	0.001	0.002
	(-0.61)	(-0.99)	(-1.38)	(-1.65)	(0.07)	(0.88)	(-0.68)	(-1.01)	(-1.62)	-(1.86)	(0.27)	(1.14)
Constant	0.016	0.014	0.006	0.005	0.004	0.007	0.016	0.014	0.007	0.006	0.003	0.005
	(1.21)	(1.05)	(1.38)	(1.17)	(0.47)	(0.77)	(1.25)	(1.09)	(1.36)	(1.17)	(0.31)	(0.6)
Country FE	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y
Year FE	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y
Observations	2070	2070	11635	11635	6354	6354	2023	2023	11154	11154	6192	6192
R-squared	0.015	0.009	0.021	0.018	0.017	0.021	0.015	0.011	0.022	0.02	0.017	0.022

Table 3.10 (continued)

Panel B Regression of subsequent quarter CAR on different measurements of standardised earnings surprises by different exclusion groups (Independent sorting)

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)
	EW_PEAD						*VW_PEAD*					
	Positive exclusion items actual GAAP EPS > actual Non-GAAP EPS		Zero exclusion items actual GAAP EPS = actual Non-GAAP EPS		Negative exclusion items actual GAAP EPS < actual Non-GAAP EPS		Positive exclusion items actual GAAP EPS > actual Non-GAAP EPS		Zero exclusion items actual GAAP EPS = actual Non-GAAP EPS		Negative exclusion items actual GAAP EPS < actual Non-GAAP EPS	
VARIABLES												
SUE_NonGAAP_std	0.013		0.02***		0.006		0.017		0.02***		0.007	
	(1.29)		(4.15)		(0.89)		(1.62)		(3.96)		(1.07)	
SUE_GAAP_std		0.031***		0.029***		0.017**		0.026**		0.029***		0.017**
		(2.89)		(5.62)		(2.35)		(2.34)		(5.38)		(2.34)
Size	0.001	0.001	0.005***	0.005***	0.002	0.002	0.001	0.001	0.004***	0.004***	0.001	0.001
	(0.75)	(0.49)	(5.86)	(5.66)	(1.53)	(1.27)	(0.7)	(0.54)	(4.55)	(4.36)	(0.78)	(0.55)
MTB	0.001	0.001	-0.001**	-0.001**	-0.001	-0.001	-0.000	-0.000	-0.002***	-0.002***	-0.001	-0.001
	(0.44)	(0.59)	(-1.96)	(-2.09)	(-1.09)	(-1.31)	(-0.22)	(-0.1)	(-2.61)	(-2.72)	(-0.91)	(-1.13)
Beta	-0.009	-0.009	-0.002	-0.001	-0.01**	-0.009*	-0.01	-0.01	-0.003	-0.003	-0.008	-0.007
	(-1.15)	(-1.11)	(-0.45)	(-0.36)	(-2.05)	(-1.86)	(-1.21)	(-1.21)	(-0.77)	(-0.69)	(-1.61)	(-1.43)
Constant	0.055	0.058	0.014	0.015	0.096***	0.1***	0.06*	0.061*	0.022	0.023	0.096***	0.1***
	(1.56)	(1.66)	(0.96)	(1.02)	(4.15)	(4.32)	(1.73)	(1.76)	(1.49)	(1.57)	(4.14)	(4.31)
Country FE	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y
Year FE	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y
Observations	2008	2008	11361	11361	6123	6123	1848	1848	10486	10486	5796	5796
R-squared	0.08	0.083	0.127	0.129	0.133	0.133	0.1	0.102	0.141	0.142	0.135	0.136

Table 3.10 (continued)

Panel C Regression of subsequent quarter CAR on different measurements of standardised earnings surprises by different exclusion groups (conditional sorting)

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)
	EW_PEAD						*VW_PEAD*					
	Positive exclusion items actual GAAP EPS > actual Non-GAAP EPS		Zero exclusion items actual GAAP EPS = actual Non-GAAP EPS		Negative exclusion items actual GAAP EPS < actual Non-GAAP EPS		Positive exclusion items actual GAAP EPS > actual Non-GAAP EPS		Zero exclusion items actual GAAP EPS = actual Non-GAAP EPS		Negative exclusion items actual GAAP EPS < actual Non-GAAP EPS	
VARIABLES												
SUE_NonGAAP_std	0.02**		0.022***		0.003		0.023**		0.02***		0.004	
	(2.00)		(4.48)		(0.44)		(2.2)		(3.88)		(0.59)	
SUE_GAAP_std		0.018*		0.028***		0.016**		0.017		0.028***		0.015**
		(1.83)		(5.67)		(2.34)		(1.62)		(5.43)		(2.16)
Size	0.001	0.002	0.005***	0.005***	0.002	0.001	0.001	0.001	0.004***	0.004***	0.001	0.001
	(0.72)	(0.79)	(5.79)	(5.81)	(1.58)	(1.12)	(0.67)	(0.76)	(4.53)	(4.50)	(0.84)	(0.44)
MTB	0.001	0.001	-0.001**	-0.001**	-0.001	-0.001	0.000	0.000	-0.002***	-0.002***	-0.001	-0.001
	(0.46)	(0.63)	(-1.98)	(-2.05)	(-1.1)	(-1.37)	(-0.21)	(-0.04)	(-2.64)	(-2.67)	(-0.91)	(-1.16)
Beta	-0.009	-0.010	-0.002	-0.002	-0.010**	-0.009*	-0.010	-0.011	-0.003	-0.003	-0.008	-0.007
	(-1.14)	(-1.17)	(-0.42)	(-0.41)	(-2.07)	(-1.82)	(-1.2)	-(1.26)	(-0.76)	(-0.74)	(-1.63)	(-1.4)
Constant	0.056	0.055	0.014	0.015	0.096***	0.1***	0.061*	0.058*	0.022	0.023	0.096***	0.1***
	(1.6)	(1.57)	(1.01)	(1.02)	(4.15)	(4.32)	(1.75)	(1.69)	(1.52)	(1.56)	(4.14)	(4.3)
Country FE	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y
Year FE	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y
Observations	2008	2008	11361	11361	6123	6123	1848	1848	10486	10486	5796	5796
R-squared	0.081	0.08	0.128	0.129	0.132	0.133	0.101	0.1	0.141	0.142	0.135	0.135

This table presents the different market reactions to GAAP and non-GAAP earnings surprises for different exclusion groups. Panel A presents the regression result of short-window CAR on different measurement of earnings surprises by exclusion groups. Panel B presents the regression result of subsequent quarter CAR on different measurement of standardised earnings surprises by exclusion groups using independent sorting. Panel C presents the regression result of subsequent quarter CAR on different measurement of standardised earnings surprises by exclusion groups using conditional sorting. The whole sample is classified into three groups according to whether the exclusion items is positive, zero or negative. Exclusion items is the difference between actual GAAP EPS and actual Non-GAAP EPS. For independent sorting, firms are first ranked and classified into 10 portfolios for each country-year according to the earnings surprise *SUE_NonGAAP* and *SUE_GAAP*, and the regression is then run within each exclusion group. For conditional sorting, firms are ranked and classified into 10 portfolios for each country-year according to the earnings surprise *SUE_NonGAAP* and *SUE_GAAP* within each exclusion group. *SUE_NonGAAP_std and SUE_GAAP_std* are standardised to the range [0, 1], and are futher subtracted by 0.5 for a median of 0. *EW_PEAD* is the equally weighted abnormal return on a stock, cumulated from 2 trading days following the announcement to 64 trading days following the announcement. *VW_PEAD* is the value-weighted abnormal return on a stock, cumulated from 2 trading days following the announcement to 64 trading days following the announcement. All continuous variables are winsorised at the top and bottom 1% of each distribution. All variable definitions are presented in Appendix A3.1. t-statistics are reported in parentheses. *, **, *** indicate significance levels (two-sided) of 10%, 5% and 1%, respectively.

Appendices of Chapter 3

Appendix A3.1 Variable Definitions

Variables	Definition	Data Source
SUE_GAAP	Analysts' GAAP earnings surprises calculated as I/B/E/S GAAP actual EPS minus the I/B/E/S last median GAAP forecast EPS, scaled by the stock price no more than 30 days prior to the earnings announcement date	Obtained from I/B/E/S
SUE_GAAP_ERROR	Previously identified GAAP earnings surprises with measurement error, calculated as I/B/E/S GAAP actual EPS minus the I/B/E/S last median non-GAAP forecast EPS, scaled by the stock price no more than 30 days prior to the earnings announcement date	Obtained from I/B/E/S
SUE_NONGAAP	Analysts' non-GAAP earnings surprises calculated as I/B/E/S non-GAAP actual EPS minus the I/B/E/S last median non-GAAP forecast EPS, scaled by the stock price no more than 30 days prior to the earnings announcement date	Obtained from I/B/E/S
SUE_GAAP_std	Decile rank of analyst' GAAP earnings surprises. Analysts' GAAP earnings surprises (*SUE_GAAP*) is assigned into 10 quintiles, the quintile ranks are further scaled to a standardised quintile rank from 0 to 1 and subtracted by 0.5 for a mythical 0 median.	Obtained from I/B/E/S
SUE_NONGAAP_std	Decile rank of analyst' non-GAAP earnings surprises. Analysts' non-GAAP earnings surprises (*SUE_NONGAAP*) is assigned into 10 quintiles, the quintile ranks are further scaled to a standardised quintile rank from 0 to 1 and subtracted by 0.5 for a mythical 0 median.	Obtained from I/B/E/S
Size	Natural logarithm of market capitalization in millions of Euros at the end of the fiscal year.	Obtained from Datastream
MTB	The ratio of market capitalisation to book value of shareholders' equity at the end of the fiscal year.	Obtained from Datastream
Beta	The volatility of a stock, estimated by the coefficient on the market index return in a CAPM model regression for firm with daily returns in the 90 trading days before the earnings announcement date.	Obtained from Datastream
EW_CAR	Equally weighted cumulative abnormal return for the three-day window [-1, 1] centred on the EAD.	Obtained from Datastream
VW_CAR	Cumulative abnormal return for the three-day window [-1, 1] centred on the EAD, adjusted for value weighted market index return.	Obtained from Datastream
EW_PEAD	Three month (2 trading days following the EAD though 64 trading days following	Obtained from Datastream

	the EAD) equally weighted cumulative abnormal return.	
VW_PEAD	Three month (2 trading days following the EAD though 64 trading days following the EAD) cumulative abnormal return, adjusted for value weighted market index return.	Obtained from Datastream

Chapter 4

Dispersion in analysts' GAAP forecasts, forecast exclusions and future stock returns

Abstract

This study investigates the relationship between dispersion in analysts' earnings forecasts and future stock returns. Specifically, dispersion in analysts' non-GAAP (General Accepted Accounting Principles) forecasts is separated into two components: dispersion in GAAP forecasts and dispersion in exclusions from GAAP. I find that both dispersion in non-GAAP forecasts and dispersion in GAAP forecasts are negatively associated with future stock returns. The reason is that current overpricing due to information asymmetry eventually leads to lower future stock returns, while another possibility is the uncertainty that increases the option value of the firm. However, the levels of disagreement on exclusions from GAAP forecasts are positively associated with future stock return. This may be due to the compensation required for higher uncertainty risk or investors may underreact to the information in earnings when analysts disagree about opinion. My findings suggest that analysts' disagreement about managers' accounting choice has important implication for investors. Future studies examining the link between analyst forecast dispersion and future return should take the differences between GAAP and non-GAAP forecasts into account.

4.1 Introduction

It is a well-established result in the literature that higher dispersion in analysts' earnings forecasts is associated with lower stock returns (Diether et al., 2002, Johnson, 2004, Veenman et al., 2020). The analysts' forecasts being used to measure the dispersion in previous studies are almost exclusively I/B/E/S non-GAAP earnings forecasts. These forecasts are based on performance measures that typically deviate significantly from GAAP earnings through the exclusion of certain line items. Because analysts generally have more freedom in adjusting the non-GAAP figures, dispersion in their non-GAAP forecasts may not precisely capture the difference in investors' opinions (Garfinkel, 2009), and may be biased due to analysts' unique incentive structure (e.g. Doukas et al., 2006). For instance, analysts may choose to converge to the consensus non-GAAP forecasts numbers because of career concerns. In contrast, and as showed in chapter 2, analysts generally have less freedom in manipulating GAAP earnings.

A recent study by Bratten et al. (2020) concludes that the variation in analysts' forecast exclusions is associated with opportunism. Firms with more income-decreasing and recurring items generally have higher dispersion in analysts' forecast exclusions, and analysts who are more experienced and have more resources tend to exclude less from their non-GAAP forecasts. Thus, the dispersion in analysts' forecast exclusions may or may not contain information about future returns.

The issue of biased analysts' views and sources of the dispersion anomaly could partially be addressed by decomposing the non-GAAP forecasts into GAAP forecasts and forecast exclusions. Previous literature often neglects the GAAP forecasts as it was not available on I/B/E/S until 2004. Bradshaw et al. (2018), however, address the importance of GAAP forecasts and find that they are informative to investors and the credibility of non-GAAP earnings is increased when GAAP forecasts are also provided. Because GAAP earnings are more regulated and analysts are less likely to manipulate them, dispersion in analysts' GAAP forecasts could a better proxy for differences in investors' opinions. According to Miller's (1977) overpricing hypothesis, in the case of strong disagreement between optimistic and pessimistic investors, stock prices will be biased upwards if pessimistic investors choose not to trade due to short-sale constraints. As a consequence, the current overpricing will eventually result in lower stock returns as stock prices revert to intrinsic value in the future. Diether et al. (2002) further explain that when rational and informed investors do not sell the overvalued stocks because of short-sale constraints, uninformed investors could subconsciously and erroneously assume that they agree with the market price. The stock price then remains upwardly biased, resulting in the lower future stock return. Combined with the findings of Bradshaw et al. (2018), these arguments suggest that higher dispersion in analysts' GAAP forecasts are associated with lower future stock returns. Hence, GAAP figures, which have been found to enhance the credibility of the non-GAAP data used in prior research, could provide new insights into the dispersion anomaly.

For a large sample of U.S. firms for the period from 2004 to 2016, I find that analysts' disagreement in non-GAAP forecasts and GAAP forecasts have a negative association with future stock returns. However, a higher level of disagreement on forecast exclusions is associated with higher future stock returns. This may be due to a compensation for higher measurement uncertainty. Alternatively, investors may be misled by analysts' intentional manipulation in forecast exclusions, thus leading to mispricing in the divergence of analysts' opinions.

To further understand the underlying explanation for the positive association between disagreements on analyst' forecast exclusions and future stock returns, I conduct two additional sub-sample tests. I first divide the sample into firms with and firms without intangible assets. This is because Barron et al. (2002) find that analysts' dispersion is higher for firms with higher levels of internally generated (and expensed) intangibles.[23] In addition, R&D expense and restructuring costs are treated as expenses in the income statement under current accounting standards, and these costs may distort the informativeness of financial information (e.g. Zarowin, 1999). I find that the positive relationship between dispersion in forecast exclusions and future stock returns is most pronounced in the subsample of firms with non-zero intangible assets. This finding indicates that when GAAP earnings numbers do not fully convey the long-run performance of firms with high intangible assets, investors may obtain useful information from the disagreement on forecast exclusions, and this disagreement captures the uncertainty risk of firms with intangible assets. However, it is also possible that investors cannot fully unravel the opportunistic behaviour of analysts, thus misprice the divergent opinions on forecast exclusions.

I then investigate the relationship of interest by partitioning the sample into firms with and without managers' non-GAAP disclosures. Managers can report their own non-GAAP figures in addition to analysts who issue non-GAAP forecasts. According to Bhattacharya et al. (2003) and Bentley et al. (2018), managers are not always consistent with analysts in reporting non-GAAP numbers. However, when they provide more explicit non-GAAP earnings figures, it acts as a benchmark and limits the potential opportunistic behaviour of analysts, because investors are able to reconcile individual analysts' forecast exclusions to actual firm disclosed exclusions. If investors still price the information from the disagreement on forecast exclusions, they might perceive it as capturing the fundamental uncertainty risk about firm value instead of accounting distortions, and require a compensation for bearing more risk. In the sub-sample tests, I find that dispersion in analysts' forecast exclusions is positively associated with future stock returns for firms with

[23] Dinh et al. (2015) find that the capitalisation of development costs is significantly associated with higher forecast dispersion under IAS 38. IFRS does not apply in the U.S., however and development costs are generally not capitalised under US GAAP.

manager-reported exclusion earnings. This relationship becomes insignificant when firms do not have manager-reported earnings exclusions. This result suggests that the uncertainty risk effect seems to matter more for the dispersion in exclusions.

This chapter contributes the literature on the analyst dispersion anomaly and analysts' non-GAAP reporting. In particular, this is the first effort to decompose dispersion in non-GAAP forecasts into dispersion in GAAP forecasts and dispersion in the exclusions component. Prior evidence suggests that firms with high dispersion in analysts' earnings forecasts earn significantly lower stock returns compared to firms with low dispersion (Diether et al., 2002; Johnson, 2020; Veenman and Verwijmeren, 2020). The analysts' forecasts that they use to measure the dispersion are non-GAAP forecasts. However, analysts' disagreement on non-GAAP forecasts may not be the most suitable proxy for different opinions among investors. The decomposition of non-GAAP forecasts into GAAP forecasts and forecast exclusions enables me to further explore the sources of the dispersion anomaly. In addition, I provide additional evidence on the implications of analysts' forecast exclusions for capital market participants. Bratten et al. (2020) investigate individual analysts' forecast exclusions and find that analysts' exclusion behaviours are associated with opportunism. My study complements this by exploring whether and how investors respond to different opinions among analysts' exclusions forecasts.

The remaining of this chapter is organized as follows. Section 4.2 reviews the literature related to analysts' non-GAAP and GAAP forecasts, and dispersion anomaly. Section 4.3 develops the hypotheses on the relationship between dispersion in analysts' forecasts and future stock return. Section 4.4 describes the sample and research design. Section 4.5 provides the descriptive details and results of empirical tests, and section 4.6 concludes.

4.2 Literature review

4.2.1 Sell-side analysts' non-GAAP and GAAP earnings forecasts

Over the past few decades, sell-side analysts' earnings forecasts have been widely used to predict earnings in practice and in capital markets-based academic accounting research. Acting as intermediaries between companies and investors, analysts generally follow specific companies and issue earnings forecasts, as well as target price and stock recommendations (Bradshaw, 2011). They facilitate the distribution of financial information and provide valuable information to market participants (Womack, 1996; Kadan et al., 2009; Loh and Stulz, 2011). Analysts' forecast revisions have been found to result in a significant market reaction (Gonedes et al., 1976; O'Brien, 1988; Philbrick and Ricks, 1991). Using the complete contents of *Institutional Investor*'s American analysts' reports, Asquith et al. (2005) examine the market reaction to the release of analyst reports and confirm that analysts provide incremental explanatory information in addition to merely interpreting information, resulting in excess returns. Beyer et al. (2010) further assert that analysts' forecasts account for 6.14% of the quarterly return.

A significant proportion of analysts, especially those who utilise I/B/E/S earnings metrics, generally refer to analysts' forecasts prepared on a non-GAAP basis. Analysts tend to adjust and exclude certain transitory items, such as gains and losses on disposals, when forecasting earnings, taking into consideration that non-GAAP earnings are more persistent than GAAP earnings (Bhattacharya et al., 2003) and are considered more useful for valuation purposes (Brown and Sivakumar, 2003). However, in principle, analysts could value a firm based on either or both GAAP and non-GAAP performance metrics. As a measurement basis that follows applicable accounting standards, GAAP earnings forecasts by analysts have received less attention, partly because of limited access to this information in earlier studies. In 2003, I/B/E/S started to include explicit GAAP earnings forecasts

(GPS), as stated in Thomson Reuters (2016): "the figure is calculated according to Generally Accepted Accounting Principles (GAAP), which is reported in SEC filings". As for the prevalence of GAAP forecasting, Bradshaw et al. (2018) found that for the period from 2003 to 2015, nearly 70% of firms with a non-GAAP forecast available also have a GAAP earnings forecast, with this percentage increasing to nearly 90% for the period 2009-2015.

Although GAAP forecasts are fairly new to the accounting literature, some previous studies have examined the items that analysts exclude from their non-GAAP forecasts. One branch of research has examined whether analysts simply mimic management to exclude items. Shane and Stock (2006) investigated whether analysts could correctly identify and interpret the temporary income effects of firms' earnings management activities. In the context of the decline in the statutory tax rate enacted in the Tax Reform Act of 1996, managers' income shifting behaviours refer to shifting income from fourth quarters in higher tax rate years to immediately following first quarters of lower tax rate years. Shane and Stock (2006) concluded that rather than consciously disregarding the income shifting behaviours, analysts are instead incapable of recognising transitory components of firm-reported earnings, and thus follow managers to exclude items as non-recurring. Chen (2010) examined whether analysts fully understand the persistence of non-GAAP exclusions, concluding that, whilst they, to a certain extent, acknowledge the persistence of exclusion items (items which managers exclude from non-GAAP earnings to meet or beat analysts' earnings forecasts), they still underestimate the persistence of other exclusions. This tendency to underestimate improves in the post-Reg G period but remains a persistent phenomenon throughout the period examined.

In contrast to these findings, other studies claim that analysts do not simply follow management to exclude items either because of opportunism or to provide investors with valuable information. For instance, Lambert (2004) argues that analysts' decisions to exclude certain items and forecast non-GAAP earnings are due to self-interest rather than for the benefit of investors. Using detailed First Call footnote data on analysts' exclusion decisions, Baik et al. (2009) found that analysts treat nonrecurring items differently for glamour stocks and value stocks. Analysts are more likely to exclude expenses for glamour stocks that should be included in non-GAAP earnings. In contrast, focusing on specific issues of recognising stock-based compensation expenses in response to SFAS 123R's requirements, Barth et al. (2012) find that unlike managers who opportunistically exclude expense to increase or smooth earnings, the primary explanation for analysts excluding expenses is that it increases their predictive abilities. Gu and Chen (2004) argue that exclusion items are less persistent and there is no evidence showing that the pricing differential between included items and exclusion items leads to abnormal future returns. Nevertheless, using hand-collected data of other exclusions or a sub-sample, Whipple (2015) finds that the items excluded by analysts are informative and relate to non-cash items that are further discounted by investors.[24] Among 563 firm-quarter observations with 963 other exclusions that Whipple hand-collected, 22% are stock based compensation, 21% are amortization, 13% are investment gains or losses and 29% are one-time items or errors in the Compustat calculation of EPS effects of special items.

Currently, debates concerning the motives and causal factors underlying analysts' tendencies to exclude certain items, including the methodology and selection framework utilised in implementing such exclusions, persist. Most previous studies are limited to particular contexts or specific settings, such as stock compensation expenses. This could be because analysts' exclusion items are ambiguous even in their reports. The dearth of explicit reconciliations between non-GAAP and GAAP earnings forecasts could also be a result of

[24] According to Whipple (2015), 'other exclusions' refer to the differences between I/B/E/S non-GAAP earnings and Compustat operating earnings (earnings prior to the influence of special items). These items are mainly comprised of recurring exclusion items.

an inability to identify and interpret certain items, or a reluctance to communicate private information truthfully. However, disaggregated forecasts have increased since the early 2000s (Bradshaw et al., 2018), including forecasts of revenues, taxes and cash flows (Givoly et al., 2009). In addition, the availability of individual analysts' GAAP forecasts on I/B/E/S further provides a chance to examine the difference between the GAAP and non-GAAP forecasts. Understanding the variation in analysts' forecast exclusions can help to better understand the incentives of analysts, and forecast exclusions can be used to test market reaction and informativeness to items representing the difference between GAAP and non-GAAP EPS.

4.2.2 Discussion of dispersion in analysts' forecasts and stock returns

Prior studies provide conflicting evidence on the relationship between dispersion in analysts' earnings forecasts and stock returns. Diether et al. (2002) and Johnson (2004) both find that there is a negative relationship between dispersion in analyst's earnings forecasts and cross-sectional stock returns. The underlying interpretation for the same result, however, differs in these two studies. Diether et al. (2002) argue that the differences of opinions among analysts reflect information asymmetry and their results reject the explanation of dispersion in analysts' earnings forecasts as a measure of risk.

Consistent with Miller's (1977) model conjecturing that stock prices reflect optimistic valuations when opinions diverge since pessimistic investors are prevented from selling the stock because of short-sale constraint and investors are assumed to be overconfident about the valuation. Diether et al. (2002) further explain that when rational and informed investors do not sell the overvalued stocks because of short-sale constraints, uninformed investors could subconsciously and erroneously assume that they agree with the market price. The stock price then remains upwardly biased, resulting in the lower future stock returns. Thus, the underlying assumption is that any frictions, including the unique incentive structure of analysts that prevent the release of negative information will lead to a negative relationship between dispersion in analysts' forecast and stock returns. However, while Diether et al. (2002) view dispersion in analysts' non-GAAP forecasts as a proxy for differences of opinion among investors, Garfinkel (2009) argue that analysts' forecast dispersion is a poor measure of different opinions among investors. Instead, this measure could be biased by analysts' complex incentive structures including career concerns (Hong and Kubik, 2003), the drive to curry favour with management (Lim, 2001), and increasing investment-banking business (Ljungqvist et al., 2006). Thus, GAAP earnings which are under strict regulation and standards may better coincide with investors' views and analysts have less freedom on playing this number.

Different from Diether et alia's (2002) interpretation, Johnson (2004) provides a risk-based explanation for the dispersion anomaly based on option-pricing theory. He argues that dispersion reflects uncertainty and proxies for the unsystematic risk (idiosyncratic risk) of a firm regarding the unobservable part of the underlying firm value. Using Fama and MacBeth (1973) regressions of monthly stock returns on forecast dispersion, Johnson (2004) also demonstrates a negative relationship between dispersion in analysts' forecasts and stock returns. His pricing model indicates that the option value will increase as the idiosyncratic risk of a firm increases. The dispersion levels reflect this risk and explains why firms with higher dispersion in analyst's earnings forecasts earn lower returns. Avramov et al. (2009) provide another interpretation of dispersion anomaly. They find that higher forecast dispersion is related to higher financial distress, and the lower future stock returns are associated with correspondingly weak credit ratings.

Following the theoretical model and empirical proxies developed by Barron et al. (1998), Barron et al. (2009) decompose the dispersion level into two components:

uncertainty and information asymmetry. The uncertainty part is represented by the errors in the mean forecasts. The information asymmetry part is represented by the variation in individual forecasts around the mean forecast. They further confirm that uncertainty rather than information asymmetry drives the negative relationship between dispersion in analysts' forecasts and stock return. However, it is noteworthy that Barron et al. (2009) measure the uncertainty part using the mean squared differences between individual analysts' forecasts (non-GAAP EPS forecast) and reported earnings per share (GAAP EPS). The error in the mean forecasts could be either non-GAAP forecast error ($\sum_{i=1}^{n}(FC_{GAAPi} - EPS)^2 /n$) or GAAP forecast error ($\sum_{i=1}^{n}(FC_{non-GAAPi} - EPS)^2 /n$). It is plausible that the misalignment between non-GAAP earnings forecasts and actual GAAP earnings numbers and measurement error may bias these results. Abarbanell and Lehavy (2007), Berger (2005) and Bradshaw et al. (2018) put forward this research design issues associated with some studies, especially, the GAAP expectation error, which results from the fact that researchers generally use I/B/E/S adjusted or unadjusted actual earnings forecasts as a proxy for GAAP earnings expectations. Cohen et al. (2007) document that the misalignment between GAAP earnings with non-GAAP earnings forecasts could lead to a downward bias in GAAP earnings response coefficients (ERCs). The "errors in variables" problem caused by measurement errors in GAAP earnings surprise could contaminate the ERC divergence result significantly by overstating the difference between the GAAP and Street ERCs. However, similar to prior studies, they do not have access to directly assess GAAP forecasts. Christensen (2007) argue that we still do not fully understand the impact of measurement error on prior findings.

While Barron et al. (2009) corroborate the uncertainty risk explanation of dispersion anomaly, a recent study by Veenman and Verwigmeren (2020) supports the investors' mispricing of earnings expectations as an explanation for the dispersion anomaly. They argue that investors' inability to unravel differences in firms' propensity to meet earnings expectations explains the negative association between dispersion in analysts' forecasts and stock returns. Specifically, when firms seek to meet analysts' exceptions by managing earnings (Jackson and Liu, 2010) or the information set provided to analysts (Gryta et al., 2016), they are more likely to increase the precision of analysts' information (Cotterr et al., 2006). In addition, analysts are likely to issue short-term pessimistic forecasts that allow firms to handily meet the expectations (Veenman and Verwijmeren, 2018). Bissessur and Veenman (2016) find that analysts are more able to do so when the level of disagreement is low. Thus, forecast dispersion is expected to be negatively related to firms' propensity to meet earnings expectations. However, investors cannot fully unravel analysts' opportunistic behaviours and this strategic interaction between managers and analysts. They misprice the earnings expectations thereafter, especially for firms with a high propensity to meet analysts' expectations (Veenman and Verwigmeren, 2020). Nevertheless, this novel interpretation is subject to certain limitations. In particular, the meet-or-beat classification is determined by the difference between actual EPS and mean consensus forecast EPS from I/B/E/S. Both are analysts' non-GAAP earnings measures. However, the appropriateness of using I/B/E/S data to proxy for managers' non-GAAP reporting is under question (Easton, 2003; Berger, 2005). For instance, Bentley et al. (2018) report that managers' and analysts' non-GAAP disclosures differ in systematic ways.

Previous research on the relationship between stock returns and dispersion in analysts' forecast generally use I/B/E/S non-GAAP performance measures that usually deviate substantially from GAAP earnings by excluding certain items, to calculate the level of dispersion. Typical exclusions are one-time items including gain and losses on disposal and extraordinary items. These are usually excluded to provide investors with more persistent and sustainable earnings (Bhattacharya et al., 2003; Nichols et al., 2005).

However, there is an increasing trend that analysts also exclude recurring items such as amortization and stock compensations (Bhattacharya et al., 2003; Whipple, 2015; Black et al., 2018)

Johnson (2004) raises a question that whether the assumed unbiased analyst's views are subject to perturbations is still on doubt. Thus, the dispersion level itself may be a function of analyst's incentive structures. Analysts may choose to converge to forecast consensus or optimistically increase their forecast earnings due to career concerns. This phenomenon is especially noteworthy since analysts have more discretion with non-GAAP performance measures. Though it is generally acknowledged that analysts provide proportionately reliable and informative non-GAAP performance measures as their performance is intimately entwined with the incentive of maximizing the value of their forecast to investors, analysts are not obliged to fully communicate their private information to investors. Empirical studies have found evidence that analysts sometimes distort their reports.

Examining analysts' affiliation with management, Dugar and Nathan (1995) find that analysts could bias their earnings forecasts to maintain a positive relationship with management, and those analysts who do not have an affiliation with management make more accurate forecasts. Michaely and Womack (1999) confirmed this by concluding that recommendations by affiliated analysts show significant evidence of bias, and the market does not recognise the full effect of this bias. Other studies attempt to recognise analysts' incentives by looking at the determinants of their performance evaluation. Hong et al. (2000a) find that analysts are less likely to gain a promotion and more likely to leave the I/B/E/S database if issuing a less accurate forecast, an effect that is more prominent for analysts who are less experienced. After controlling for forecast accuracy, Hong and Kubik (2003) document that there is a higher probability for analysts who issue an optimistic earnings forecasts to move to a top tier brokerage house. Overall, therefore, analysts' non-GAAP forecasts that previous literature often uses to calculate dispersion could be distorted due to analysts' incentives and may bias previous results.

The issue of biased analysts' views could be scrutinised by separating the non-GAAP earnings forecasts into two components: GAAP earnings forecasts and forecast exclusions. Bratten et al. (2020) directly examine the relationship between analysts' characteristics and exclusion behaviours on an individual analyst level. They obtain data from 2004 to 2016 and test the association between variation in analysts' forecasted exclusions and various excluded GAAP earnings items. The results show that analysts' exclusions are associated with opportunism, and analysts who are more experienced and with more resources tend to exclude less from their non-GAAP forecast, especially income-decreasing and recurring items. The underlying assumption is that analysts with more experience and resources are less concerned about currying favour with management, and thus exclude fewer items than inexperienced analysts. Furthermore, GAAP forecast accuracy decreases as the magnitude of analysts' forecast exclusions increases. This is consistent with Doyle et al. (2003) who argue that special items and one-time items are more defendable and justifiable while the motivation for excluding recurring items by analysts is less clear. Nevertheless, the negative future cash flow is related to recurring exclusion items.

Although Bratten et al. (2020) provide insight into analysts' forecast exclusions, whether the market can properly identify this opportunism and whether investors are misled by different opinions in analysts' forecasted exclusions remains unknown. As Doyle et al. (2003) state, there is a chance that investors are misled by opportunistically adjusted earnings figures. Beyer et al. (2010) also indicate that due to insufficient information about analysts' incentives, users of analysts' reports are generally unable to fully anticipate the bias in these reports. However, they do to a certain extent take analysts' incentives into consideration when making inferences about firm performance. Thus, the role of dispersion in analysts' GAAP forecasts and dispersion in exclusions in predicting the cross section of future returns is worthy of further examination.

4.3 Hypothesis Development

As GAAP earnings forecasts are produced according to a comparatively rigid set of accounting standards and analysts are assumed to have less freedom to choose their own accounting definitions, consistent with Diether et al. (2002), my first hypothesis views dispersion in GAAP forecasts as a proxy for differences of opinion among investors.

Miller (1977) argues that short-sale constraints prevent pessimistic investors from selling the stock when opinions diverge, and optimistic demand pushes stock prices up. This further results in lower stock returns when stock price is eventually adjusted downwards. Diether et al. (2002) further develop this idea and argue that any friction that prevents the release of negative opinions will produce the negative relation between dispersion in forecasts and future returns since the market price will be upwardly biased.

Though Miller's (1977) underlying assumption of "optimistic investors" indicates they may be overconfident, Diether et al. (2002) claim that investors who are not overconfident may erroneously interpret the behaviours of informed investors. Specifically, the informed investors may not be able to trade to correct for the mispricing because of trading cost and short-sale constraints, but other investors may assume that the informed investors agree with the current price and thus do not revise valuation downwardly. This eventually results in the current market price not incorporating negative information correctly and is upwardly biased. In another aspect, unfavourable news is usually not disclosed to a full extent (Hong et al., 2000b) though analysts disagree more on this negative news (Ciccone, 2003). Possible reasons could be that analysts choose to stop covering the stock (McNichols and O'Brien, 1977) when they are extremely pessimistic, or they are often reluctant to communicate negative news with investors due to the incentive to please managers. In either case, for firms associated with higher divergence of opinions, the current market prices may not fully reflect the negative information but are upwardly biased, which eventually result in lower return.

The recent study by Bradshaw et al. (2018) addresses the importance of GAAP forecasts and suggests that the credibility of non-GAAP earnings is increased when GAAP forecasts are also provided. In addition, Cain et al. (2020) warn that dispersion in analysts' non-GAAP forecasts may be correlated with managers' non-GAAP reporting, while managers are likely to mis-classify recurring expenses as non-recurring. As discussed above, dispersion in GAAP forecasts can be a proxy for differences of opinion among investors, thus, I assume that firms with higher dispersion in analysts' GAAP forecasts will have lower future stock returns. My first hypothesis is stated as follows:

H4.1: *Stocks with higher dispersion in analysts' GAAP forecasts have lower future returns.*

In consideration of the forecast exclusions, currently there is little literature exploring this question. It is still unclear whether the dispersion in forecast exclusions reflects the uncertainty or the disagreement on accounting regime. It could also result from the fact that some analysts may opportunistically adjust earnings numbers. Bratten et al. (2020) find that the variation in exclusions is associated with analyst opportunism. Their evidence also shows that firms with more income-decreasing and recurring items have higher dispersion in analysts' forecast exclusions. Analysts may choose not to fully and truly report and communicate their private information with investors due to their unique incentive structure. Specifically, analysts may ignore or discount private information because of career concerns (Trueman, 1994), incentives to curry favour with managers (Lim,

2001) and incentives to increase investment banking business (Richardson et al. 2004). In this case, some analysts may choose to issue more favourable or bearable street earnings forecasts through excluding more income-decreasing items. As found by Bratten et al. (2020), those analysts who have greater resources and are more experienced are less likely to be associated with income-decreasing and recurring excluding items since they are less concerned about currying favour with management. Therefore, different from the underlying assumption of hypothesis 4.1, the dispersion in forecast exclusions may not act as a proxy for differences of opinion among investors in this situation but may act as a proxy for analyst opportunism. If investors are aware of this opportunistic exclusion behaviour and are not misled by earnings measures that are adjusted by analysts, the current stock price and future stock returns could be independent from the current level of disagreement about the exclusion items.

However, if the dispersion in analyst' forecast exclusions reflects the uncertainty risk or investors simply underreact to the information for firms with higher dispersion in exclusion, it could result in a positive relationship between dispersion in analyst' forecast exclusions and future return. It is possible that dispersion in exclusions could capture uncertainty risk and investors require compensation for future stock return. The uncertainty and imperfection of the market could lead to the appearance of risk premium. Merton (1987)'s model predicts a positive relationship between stock returns and idiosyncratic risk and Fu (2009)'s empirical evidence further supports this. Furthermore, it is also plausible that investors underreact to the information for firms with higher dispersion in exclusion as analysts disagree more. The current stock price could then be downwardly biased, further resulting in a higher future return when stock price eventually corrects upward. To test this prediction, my second hypothesis, stated in the null form is as follows:

H4.2: *The dispersion in analysts' forecast exclusions is not associated with future* *stock returns.*

4.4 Research Design

4.4.1 Data and sample characteristics

The sample begins in January 2004 since GAAP earnings forecasts became available in Institutional Brokers Estimate System (I/B/E/S) in 2003 and the sample period is from January 2004 to December 2016. The statistics include NYSE, AMEX and Nasdaq stocks. The data on individual analyst' GAAP forecasts and non-GAAP forecasts are taken from I/B/E/S Detailed History. Stock return is acquired from CRSP and fundamental accounting information including market value and book value of equity are acquired from COMPUSTAT. To be included in my final sample, the firm is required to have data available on I/B/E/S, CRSP and COMPUSTAT and is covered by at least two analysts. The final sample consists of 202,666 firm-month observations on U.S. firms

Exclusions are calculated using non-GAAP earnings forecasts minus GAAP earnings forecast. Individual analyst' forecasts are retrieved from *Detail History* file of I/B/E/S. As Diether et al. (2002) identify, the forecast data from *Summary History* file is adjusted historically for stock splits to provide smooth time series earnings forecast. Using detail forecast data is more suitable for this research especially, the average and standard deviations of individual forecasts are calculated each month.

I use individual forecasts from Detailed History I/B/E/S file to calculate the dispersion measures. If analysts make more than one forecasts in a given month, only the latest forecast is retained. Each analyst record includes a revision date which is the date that the forecast was last confirmed. I extend the current forecast until its revision date. For example, if a forecast is made in January and the revision date is in March and if there is no updated forecast by the same analyst for the firm of interest during this period, this forecast number will be used in the computation of dispersion for January, February and March.

However, in some records, the gap between forecasts announcement date and revision date is too long (for example, more than 360 days). Therefore, I only retain the forecast to calculate dispersion for up to six months from the date the forecast is issued. In cases of an error in I/B/E/S that a revision date precedes the forecast date, I follow Diether et al. (2002) to use the earnings forecasts only for the month it is issued.

4.4.2 Regression analysis

Following Diether et al. (2002), Johnson (2004) and Barron et al. (2009), I use regression models to examine the relationship between stock returns and dispersion in analysts' non-GAAP forecast, dispersion in analysts' GAAP forecasts and dispersion in analysts' forecast exclusions respectively.

Specifically, stocks are assigned to portfolios (five quantiles) based on characteristics including dispersion in non-GAAP forecasts, dispersion in GAAP forecasts, dispersion in forecast exclusions, size and book to market ratio. After variables are assigned into quintiles, the quintile ranks are further scaled to a standardised quintile rank from 0 to 1 following Barron et al. (2009). All variables are winsorised at level 1% and 99%.

Following Johnson (2004) and Barron et al. (2009), I use monthly Fama-Macbeth regressions (1973) of stock returns on measures of analysts forecast dispersion, size and book to market ratio quintile rank. The Fama-Macbeth method estimates the betas and risk premia for any risk factors that are expected to determine asset prices. The dependent variable is the monthly stock returns following the month in which forecast dispersion and its components are measured. Stocks in each month are assigned quintiles based on dispersion, size and book to market ratio independently. Measures are transformed into standardised ranks and are used for all the independent variables in the regression. Size and book to market ratio are measures at the end of the prior fiscal year-end. Fama- Macbeth cross-sectional regressions are estimated every month from January 2004 through December 2016. All variable definitions are presented in Appendix A4.1

4.5 Results

4.5.1 Descriptive statistics

Table 4.1 reports the descriptive statistics for the whole sample from January 2004 to December 2016. All variables require non-missing data from I/B/E/S, COMPUSTAT and CRSP database. The sample consists of 202,666 firm-month observations on U.S. firms. According to Table 1, the average monthly stock return is 1% and the standard deviation of stock returns is 11.4%. Half of the firms in this sample earn a monthly return lower than 0.9%. This sample includes relatively large firms with mean market value of $8,522 million and a median market value of $1,910 million. This size bias is due to the requirement of the data belonging to the intersection of CRSP, COMPUSTAT and I/B/E/S. The average book to market ratio is 0.529 with a minimum of -0.291 and maximum of 2.551. Regarding the variables of interest, the mean value of dispersion in analysts' non-GAAP forecasts (*Dis_nonGAAP*) is 0.021, indicating that on average, the standard deviation of analysts' one year ahead adjusted earnings per share (EPS) forecasts is 2.1% of stock price. In comparison, the mean value of dispersion in analysts' GAAP forecasts (*Dis_GAAP*) is slightly higher, at 0.026 or 2.6%. The median is 0.003, which is also higher than the median of *Dis_nonGAAP* (0.002). This is reasonable: when making GAAP forecasts, analysts are supposed to consider the potential exclusions that are more difficult to forecast.

The dispersion in forecast exclusions (*Dis_Ex*), with mean value of 0.01 and median of 0.001, is smaller than the dispersion in non-GAAP or GAAP earnings forecast. This could result from the fact that exclusions are largely attributable to non-recurring items (Bradshaw and Sloan, 2002), and recurring items generally occupy a small part proportion of earnings.

The mean adjustment (*Meanadj*), which is the difference between non-GAAP earnings forecasts and GAAP earnings forecasts scaled by stock price, has a mean value of 0.01 and median value of 0.000. This suggests that on average, analysts' non-GAAP forecasts are greater than GAAP forecast, with a difference of around 1% of stock price. This average upward adjustment may provide investors with more valuable information on operational performance (Chen, 2010), but may also be consistent with Baik et alia's (2009) study, which finds that analysts announce higher non-GAAP performance metrics because of the opportunistic incentives such as currying favour with managers.

In order to explore the association between stock returns and dispersion in analysts' forecasts, I first adopt a standard approach in asset pricing pioneered by Jegadeesh and Titman (1993). Specifically, each month, I assign stocks to five portfolios (*D1* to *D5*) based on dispersion in analysts' forecasts as of the previous month. Stocks with the highest dispersion are assigned to group *D5* and stocks with the lowest dispersion are assigned to group *D1*. I then compute the equally weighted monthly buy and hold stock returns for each portfolio.

Table 4.2 reports the mean portfolio returns by dispersion in analysts' forecasts. The first column (1) of table 4.2 shows that when ranking by dispersion in analysts' non-GAAP forecasts, the difference between the average monthly stock return of *D5* group and that of *D1* is -0.5%, and is statistically significant at 1 percent. When ranking the portfolios based on dispersion in analysts' GAAP forecasts and dispersion in forecast exclusions, this return difference on the *D5-D1* strategy for column (2) and (3) is -0.49%, and -0.25% respectively, and both are statistically significant at the 1% level. Thus, a portfolio in the highest rank of dispersion in analysts' forecasts underperforms a portfolio in the lowest rank of dispersion in analysts' forecasts. This indicates that there is a negative relationship between stock returns and dispersion in analysts' earnings forecasts. However, this evidence does not take into consideration other risk characteristics that can affect stock returns (for example, the common measures of risk that are well documented in the literature include firm size and book to market ratio (Fama and French, 1995; Barber and Lyon, 1997)).

4.5.2 Stock returns and dispersion in analysts' forecasts

In this section, following Johnson (2004) and Barron et al. (2009), I further analyse the relationship between stock return and dispersion in non-GAAP forecasts, dispersion in GAAP forecasts and dispersion in forecast exclusions respectively using Fama and MacBeth (1973) regressions. Size and book to market ratio are introduced as control variables here and are measured as the end of the prior year. Consistent with Barron et al. (2009), I assign stocks to quintiles based on dispersion, size and book to market ratio separately and further scale it to the [0, 1] range. The monthly return is regressed on dispersion and other control variables in the prior month. The whole sample consists of 202,666 observations and 156 months from January 2004 to December 2016.

Table 4.3 presents the correlation matrix for the variables used in the regressions. Consistent with hypothesis 4.1, the correlation between *Ret* and *Dis_GAAP_qr* is significantly negative (-0.0145). The significant negative correlation between *Ret* and *Dis_nonGAAP_qr* (-0.0148) is consistent with previous findings that stocks with higher dispersion in analysts' non-GAAP forecasts earn lower future stock returns. *Size_qr* is significantly and negatively correlated with *Dis_nonGAAP_qr* (-0.2915) and *Dis_GAAP_qr* (-0.2059), indicating that larger firms generally have lower dispersion in analysts' forecasts. Because larger firms have more publicly available information (Bhushan, 1989) and more analysts following them, these firms have relatively lower information asymmetry (Yohn, 1998), thus the magnitude of disagreement among analysts' forecasts is smaller. With the exception of *Dis_nonGAAP_qr* and *Dis_GAAP_qr* being highly correlated (0.7376), other correlations suggest that multicollinearity is not likely to be a serious problem in the regression.

Table 4.4 presents the Fama-MacBeth regression results. The coefficients are time-series mean coefficients. In column (1), the coefficient on the quintile rank of dispersion in non-GAAP earnings forecasts (*Dis_nonGAAP_qr*) is -0.0086. This negative coefficient is consistent with the evidence in Diether et al. (2002), Johnson (2004) and Barron et al. (2009) that there is a negative relationship between stock returns and dispersion in analysts' non-GAAP forecasts.

In column (2), the coefficient on the quintile rank of dispersion in GAAP earnings forecasts (*Dis_GAAP_qr*) is -0.0076 and significant at 1% level. This result is consistent with hypothesis 4.1 and indicates that larger differences in opinions on GAAP earnings forecasts are also associated with lower future stock returns. When separately including only the quintile rank of dispersion in exclusions (*Dis_Ex_qr*) as independent variable in column (3), the coefficient becomes insignificant. This could be driven by the fact that forecast exclusions are usually considered together with the fundamental GAAP forecasts. Dispersion in forecast exclusions itself may reflect less information and the association with future stock returns becomes insignificant. In column (4), the coefficients on *Dis_GAAP_qr* remains negative (-0.0090) and the coefficients on forecast exclusions becomes positive (0.0032) and significant at 5% level. The R^2 changes modestly from 3.4% in column (2) to 3.8% in column (4), reflecting that though very small, dispersion in forecast exclusions has an incremental explanatory power for the variation in stock price.

Consistent with Barron et al. (2009), coefficients on size quintile rank (*Size_qr*) and book to market ratio quintile rank (*BTM_qr*) are insignificant in four models. This could result from the requirement that the sample has both GAAP and non-GAAP forecasts and satisfies the requirement of other data availability, so the sample consists relatively large firms with mean market value $8,522 million and lower book to market ratios. Another possibility is that dispersion factors subsume these size and book to market factors.

The positive coefficient on *Dis_Ex_qr* in column (4) can be consistent with the argument that divergent opinions on forecast exclusions captures the uncertainty risk and idiosyncratic volatilities on the firm. Investors generally do not hold diversified portfolios in reality and require a return compensation for bearing higher idiosyncratic risk. Merton's (1987) model predicts this positive relationship between stock returns and idiosyncratic risk and Fu's (2009) empirical evidence further supports this using EGARCH model to estimate the idiosyncratic volatilities. Earnings exclusions generally include more one-time items and items that are more difficult to forecast and could reflect analysts' evaluation of firm's future potential uncertainty. Nevertheless, there is also another possibility, namely that investors simply underreact to the information in earnings when analysts' opinions diverge as they could be uncertain about the reliability of the information, especially when analysts have more freedom in adjusting forecast exclusions. In this case, undervalued current stock price could lead to higher future return as stock price corrects upward. Therefore, the findings regarding dispersion of exclusions could be consistent with both uncertainty risk and mispricing arguments. It is also important to note that this result is not necessarily contradictory to Bratten et al.'s (2020) finding that exclusions are associated with opportunism. The reason is that higher variation in exclusions could be caused by some analysts excluding more income-decreasing items due to career concerns or unique incentives. This could be viewed by investors as uncertainty and they may also underreact to earnings information if taken this behaviour into consideration.

4.5.3 The effect of firm characteristics on the relationship between stock returns and dispersion in analysts' forecast

To further understand the underlying explanation for the positive association between disagreements on analyst' forecast exclusions and future stock return, I divide the sample into two groups according to firm characteristics, specifically intangible assets. Srivastava (2014) documents the decline in earnings quality over past 40 year and ascribe this to possible higher intangible intensity. Lev and Gu (2016) also argue that traditional financial reports become less useful over years and recent studies show that this is especially for companies that hold large intangibles. The underlying reason is that current accounting standards do not allow firms to capitalise intangible investments and such investment as R&D expense and restructuring costs are treated as expense on income statement. Lev and Zarowin (1999) argue that these are not matched with the revenues in later years and consequently distort the informativeness of financial information. However, analysts in their forecasted non-GAAP earnings numbers can exclude items such as restructuring charges, stock-based compensation and they may have more disagreement when treating these items for firms with intangible assets. According to Barron et al. (2002), analysts' dispersion is positively associated with the levels of firms' intangibles. In addition, intangible assets usually contain more complex information and are more difficult to value due to the high uncertainty (Gu and Wang, 2005). Therefore, it is expected that the exclusion dispersion-return relationship is stronger among firms with higher intangible assets.

Table 4.5 presents the analysis for sub-samples. Columns (1) and (3) in Table 4.5 present results for firms without intangible assets and columns (2) and (4) show the results for firms with intangible assets. When regressing the stock returns on dispersion in analysts' non-GAAP forecasts, the coefficient on *Dis_nonGAAP_qr* is significantly higher (i.e., less negative) (-0.0059) in column (1) compared to the coefficient (-0.0222) in column (2), indicating that the negative relationship between stock returns and dispersion in analysts' non-GAAP forecasts is stronger for firms without intangible assets compared to firms with intangible assets.[25] Compared to the insignificant coefficients on *Dis_Ex_qr* in column (3) (0.0010), the coefficient is 0.0039 in column (4) and significant at the 5% level. This indicates that when GAAP earnings numbers may not fully convey the long-run performance of firm with high intangible assets, investors could obtain useful information from the disagreement on forecast exclusions, and this disagreement captures the uncertainty risk of firms with intangible assets. However, I cannot completely rule out the possibility that investors may be misled by analysts' intentional manipulation on forecast exclusions.

4.5.4 The effect of managers' reported exclusion earnings on the relationship between stock returns and dispersion in analysts' forecast

In this section, I explore whether the positive relationship between stock returns and dispersion in analysts' forecast exclusions is affected by managers' choices to report exclusion earnings. Analysts can have different opinions on whether certain components of GAAP earnings should be included or excluded from non-GAAP earning (Baik et al., 2008) and these decisions are often subjective (Gu and Chen, 2004). Managers, however, can report their own non-GAAP figures and this can differ from analysts' non-GAAP earnings data available on I/B/E/S (Berger et al., 2010). Bhattacharya et al. (2003) find that managers disagree with I/B/E/S reported non-GAAP earnings for one-third of their hand-collected sample. Bentley et al. (2018) further explore this important question by creating the first large-sample data set of managers' non-GAAP earnings disclosure. They find that although managers' and analysts' non-GAAP figures overlap, 23% of the I/B/E/S non-GAAP metrics

[25] In untabulated analysis, the chow test is used to test whether the coefficients on *Dis_nonGAAP_qr* of column (1) and column (2) are significantly different. The chow test statistics is 168.56, and it is significant at 1% level.

are not explicitly reported by managers. Because analysts mainly receive information from managerial disclosures and detailed earnings disclosures allow analysts to filter out certain earnings components, managers' reported non-GAAP performance metrics act as a benchmark and further limits the potential opportunistic behaviour of analysts. This motivates my analysis of sub-samples of managers' exclusion disclosures. The publicly available data on managers' non-GAAP reporting from Bentley et al. (2018) allows me to identify whether managers' report exclusion earnings in the sample periods.

Table 4.6 reports the regression results. I introduce a dummy variable *Mgr_Exl* that takes the value of 1 if manager reports exclusion earnings, and otherwise 0. Columns (1) and (3) in Table 4.6 present the analysis for firms without managers' non-GAAP disclosures and columns (2) and (4) show the results firms with managers' non-GAAP disclosures.

The coefficient on *Dis_nonGAAP_qr* in column (1) is -0.0099 and significant at the 1% level and -0.0059 in column (2) and significant at the 10% level, indicating that when firms report non-GAAP earnings, the association between analysts' disagreement on non-GAAP earnings forecasts and future stock price is weaker.

This could be ascribed to the lower information asymmetry when managers provide information on excluded earnings components. When regressing the future stock returns on *Dis_GAAP_qr* and *Dis_Ex_qr*, the coefficient on *Dis_Ex_qr* is insignificant (0.0020) in column (3) but significantly positive (0.0068) at the 10% level in column (4). This result provides suggestive evidence on the uncertainty risk effect of dispersion in forecast exclusions. When firms provide non-GAAP earnings disclosures, investors are able to reconcile analysts' forecast exclusions to managers' excluded earnings components and the benchmark role of managers' exclusion disclosures could help to lower the risk of analysts' opportunistic behaviour. If investors still price the information from the disagreement on forecast exclusions, they might perceive it as capturing the fundamental uncertainty risk about firm value instead of accounting distortions, and require a compensation for bearing more risk.

4.6 Conclusion

Prior research indicates that the divergence of opinion between analysts is negatively associated with future stock returns (Abarbanell, Lanen and Verrecchia, 1995; Johnson, 2004; Doukas et al., 2006; Barron et al., 2009). The analysts' forecasts being used to compute the dispersion in previous studies refers to the non-GAAP earnings forecasts. This chapter separates the dispersion in analysts' non-GAAP forecasts into dispersion in analysts' GAAP forecasts and dispersion in exclusions' forecasts, and evaluates the association between dispersion in analysts' forecasts and future stock returns. The availability of GAAP forecasts on I/B/E/S since 2004 enables me to provide more insights into analysts' GAAP forecasts and forecast exclusions. I find that both dispersion in non-GAAP forecasts and dispersion in GAAP forecasts are negatively associated with future stock returns. Because analysts have less freedom in adjusting the GAAP numbers, dispersion in GAAP forecasts could better proxy for differences of opinion between investors. When opinions diverge, stock prices are currently overpriced due to information asymmetry (Miller, 1977; Diether et al., 2002), and this leads to future lower stock return.

In addition, I find that the levels of disagreement on exclusions from GAAP forecasts are positively associated with future stock return. This may result from the compensation required for higher uncertainty risk or mispricing of divergence of analysts' opinion. In additional sub-sample tests of the effect of managers reported exclusion earnings on the relationship between stock returns and dispersion in analysts' forecast exclusions, the evidence suggests that disagreement on forecast exclusions may capture the uncertainty risk. Overall, my findings suggest that analysts' disagreement about managers' accounting choice has important implication for investors. I also provide further evidence on the role of dispersion of analyst' GAAP forecasts and dispersion of exclusions in predicting the cross-sectional future returns. The differences between GAAP and non-GAAP forecasts should be emphasized in future studies aiming to investigate the analysts' forecasts dispersion. However, the findings could be limited as the control variables applied in the return predictability tests include only firm size and book to market ratios. Future research may add more control variables such as market beta, momentum factor and analysts' coverage to test the return predictability of analysts' disagreement on different earnings metrics.

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Tables of Chapter 4

Table 4.1 Descriptive statistics

	N	Mean	S.D.	Min	Median	Max
Ret	202,666	0.01	0.114	-0.326	0.009	0.382
Size	202,666	8522.32	20566.96	55.672	1910.154	144684.2
Ln_size	202,666	7.633	1.674	4.019	7.555	11.882
BTM	202,666	0.529	0.45	-0.291	0.423	2.551
Dis_nonGAAP	202,666	0.021	0.09	0.000	0.002	0.772
Dis_GAAP	202,666	0.026	0.11	0.000	0.003	0.934
Dis_Ex	202,666	0.010	0.038	0.000	0.001	0.314
Meanadj	202,666	0.010	0.038	-0.044	0.000	0.302

This table presents descriptive statistics for the full sample with winsorisation. Extreme values are replaced with 1st and 99th percentile values. *Ret* is the one-month ahead monthly stock return. *Size* is total market value at the end of the prior fiscal year. *Ln_size* is the natural logarithm of total market value (in $m) at the end of the prior fiscal year. *BTM* is book to market ratio calculated as book value divided by market value. Book value is the total stockholders' equity at the end of the prior fiscal year. *Dis_nonGAAP* is dispersion in analysts' non-GAAP forecasts measured as the standard deviation of analyst's non-GAAP forecasts scaled by stock price at the end of the prior month. *Dis_GAAP* is dispersion in analysts' GAAP forecasts measured as the standard deviation of analysts' GAAP forecasts scaled by stock price at the end of the prior month. *Dis_Ex* is dispersion in analysts' forecast exclusions measured as the standard deviation of analysts' forecast exclusions scaled by stock price at the end of the prior month. *Meanadj* is analysts' average forecast exclusions calculated as the mean value of forecast exclusions divided by stock price at the end of the prior month. All variable definitions are presented in Appendix A4.1.

Table 4.2 Mean portfolio returns by dispersion in analyst' forecasts

	Mean Returns		
	Performance metrics		
Dispersion Quintiles	(1) Dispersion in Non-GAAP forecast	(2) Dispersion in GAAP forecast	(3) Dispersion in Exclusion forecast
D1 (low)	0.0111	0.0110	0.0106
D2	0.0115	0.0120	0.0105
D3	0.0117	0.0110	0.0102
D4	0.0097	0.0102	0.0105
D5 (high)	0.0061	0.0061	0.0081
D5-D1	-0.0050***	-0.0049***	-0.0025***
t-statistic	(-5.71)	(-5.64)	(-3.28)

This table reports the mean portfolio returns by dispersion in analysts' forecasts. Each month, stocks are sorted into five groups based on dispersion in analysts' earnings forecasts for the previous month. Stocks with highest dispersion are assigned to group *D5* and stocks with lowest dispersion are assigned to group *D1*. Mean portfolio return is the equally weighted one-month buy and hold return. Dispersion in analysts' forecasts is defined as the standard deviation of analysts' forecast scaled by stock price at the end of the prior month. *t*-statistics are reported in parentheses *, **, *** indicate significance levels (two-sided) of 10%, 5% and 1%, respectively.

Table 4.3 Correlation matrix

Variables	*Dis_nonGAAP_qr*	*Dis_GAAP_qr*	*Dis_Ex_qr*	*Size_qr*	*BTM_qr*
Ret	-0.0148***	-0.0145***	-0.0064***	-0.0101***	0.0124***
Dis_nonGAAP_qr		0.7376***	0.1771***	-0.2915***	0.2499***
Dis_GAAP_qr			0.3752***	-0.2059***	0.2223***
Dis_Ex_qr				0.1706***	0.0731***
Size_qr					-0.2081***

This table reports the Pearson correlation matrix for the variables used in the regressions. *Ret* is the monthly stock returns following the month in which forecast dispersion is measured. *Dis_nonGAAP_qr* is the quintile rank of analysts' dispersion in non-GAAP forecasts. *Dis_GAAP_qr* is the quintile rank of analyst' dispersion in GAAP forecasts. *Dis_Ex_qr* is the quintile rank of analysts' dispersion in forecast exclusions. Dispersion in analysts' forecasts is measured as the standard deviation of analyst' forecasts scaled by stock price at the end of the prior month. *Size_qr* is the quintile rank of firm size. Firm size is measured as the total market value at the end of the prior fiscal year. *BTM_qr* is the quintile rank of book to market ratio. The book to market ratio is calculated as book value divided by market value. Book value is the total stockholders' equity at the end of the prior fiscal year. *, **, *** indicate significance levels (two-sided) of 10%, 5% and 1%, respectively.

Table 4.4 Fama-Macbeth regression results

Variables	Stock return *Ret* (1)	Stock return *Ret* (2)	Stock return *Ret* (3)	Stock return *Ret* (4)
Dis_nonGAAP_qr	-0.0086***			
	(-3.16)			
Dis_GAAP_qr		-0.0076***		-0.0090***
		(-3.11)		(-3.62)
Dis_Ex_qr			-0.0005	0.0032**
			(-0.31)	(2.15)
Size_qr	-0.0003	0.0007	0.0019	- 0.0000
	(-0.11)	(0.25)	(0.66)	(-0.01)
BTM_qr	0.0007	0.0003	-0.0012	0.0001
	(0.27)	(0.11)	(-0.45)	(0.05)
Constant	0.0113**	0.0106**	0.00768	0.0103**
	(2.34)	(2.14)	(1.46)	(2.08)
Observations	202,666	202,666	202,666	202,666
R-squared	0.036	0.034	0.029	0.038
Number of groups	156	156	156	156

This table presents the Fama-Macbeth regression results of regressing monthly stock returns on dispersion in analysts' forecasts. Fama-Macbeth (1973) cross-sectional regressions are run every month from Jan 2004 to Dec 2016. Stock return is regressed on quintile rank of dispersions in analysts' non-GAAP forecasts, dispersions in analysts' GAAP forecasts, dispersions in analysts' forecast exclusions, size and book to market ratio. The sample consists of 202,666 firm-month observations. The dependent variable is monthly stock return following the month in which forecast dispersion is measured. All stocks are assigned a quintile rank based on *Dis_nonGAAP*, *Dis_GAAP*, *Dis_Ex*, *Size* and *BTM*. These quintile ranks are further scaled to 0 to1 and used for all variables in the regressions. All variable definitions are presented in Appendix A4.1. *t*-statistics are reported in parentheses *, **, *** indicate significance levels (two-sided) of 10%, 5% and 1%, respectively.

Table 4.5 Fama-Macbeth regression results-- Two groups based on Zero/Non-zero intangible assets to size ratio

	Ret			
Variables	*Intangible=0* (1)	*Intangible=1* (2)	*Intangible=0* (3)	*Intangible=1* (4)
Dis_nonGAAP_qr	-0.0222***	-0.0059**		
	(-2.76)	(2.34)		
Dis_GAAP_qr			-0.0143**	-0.0078***
			(-2.15)	-(3.29)
Dis_Ex_qr			0.0010	0.0039**
			(0.22)	(2.65)
Size_qr	0.0059	-0.0008	0.0031	-0.0014
	(0.85)	(-0.32)	(0.49)	-(0.52)
BTM_qr	0.0005	-0.0001	0.0080	-0.0006
	(0.06)	(-0.05)	(1.17)	-(0.26)
Constant	0.0097	0.0112**	0.0077	0.0108**
	(1.10)	(2.35)	(1.04)	(2.17)
Observations	29,584	170,048	29,584	170,048
R-squared	0.109	0.036	0.134	0.037
Number of groups	156	156	156	156

This table presents the Fama-Macbeth regression results of regressing monthly stock return on dispersion in analysts' forecasts for firms with intangible assets and without intangible assets. Fama-Macbeth (1973) cross-sectional regressions are run every month from Jan 2004 to Dec 2016. Stock return is regressed on quintile rank of dispersions in analysts' GAAP forecasts, dispersion in analysts' forecast exclusions, size and book to market ratio. The sample consists of 29,584 for firms without intangible assets, and 170,048 for firms with intangible assets. The dependent variable is monthly stock return following the month in which forecast dispersions are measured. *Intangible* is a dummy variable that takes the value of 1 if firms have intangible assets, and otherwise 0. All stocks are assigned a quintile rank based on *Dis_GAAP, Dis_Ex, Size* and *BTM*. These quintile ranks are further scaled to 0 to1 and used for all variables in the regressions. All variable definitions are presented in Appendix A4.1. *t*-statistics are reported in parentheses *, **, *** indicate significance levels (two-sided) of 10%, 5% and 1%, respectively.

Table 4.6 Fama-Macbeth regression results--Two groups based on manager reported exclusion earnings

Variables	*Ret*			
	Mgr_Exl=0 (1)	*Mgr_Exl*=1 (2)	*Mgr_Exl*=0 (3)	*Mgr_Exl*=1 (4)
Dis_nonGAAP_qr	-0.0099***	-0.0059*		
	(3.12)	(1.73)		
Dis_GAAP_qr			-0.0010***	-0.0077**
			(3.40)	(2.21)
Dis_Ex_qr			0.0020	0.0068*
			(-1.36)	(1.91)
Size_qr	0.0008	-0.0019	0.0004	-0.0012
	(0.25)	(0.63)	(0.13)	(0.37)
BTM_qr	0.0012	-0.0009	0.0011	-0.0014
	(0.36)	(0.30)	(0.34)	(-0.48)
Constant	0.0100*	0.0115**	0.0099*	0.0093*
	(1.92)	(2.20)	(1.80)	(1.68)
Observations	82,567	77,990	82,567	77,990
R-squared	0.048	0.052	0.051	0.058
Number of groups	149	148	149	148

This table presents the Fama-Macbeth regression results of regressing monthly stock return on dispersion in analysts' forecasts for firms with manager reported exclusion earnings and firms without manager reported exclusion earnings. Fama-Macbeth (1973) cross-sectional regressions are run every month from Jan 2004 to Dec 2016. Stock return is regressed on quintile rank of dispersion in analysts' non-GAAP forecasts, dispersions in analysts' GAAP forecasts, dispersions in analysts' forecast exclusions, size and book to market ratio. The sample consists of 77,990 observations for firms with manager reported exclusion earnings, and 82,567 observations for firms without manager reported exclusion earnings. The dependent variable is monthly stock return following the month in which forecast dispersion is measured. *Mgr_Exl* a dummy variable that takes the value of 1 if manager reports exclusion earnings, and otherwise 0. All stocks are assigned a quintile rank based on *Dis_nonGAAP, Dis_GAAP, Dis_Ex, Size* and *BTM*. These quintile ranks are further scaled to 0 to1 and used for all variables in the regressions. All variable definitions are presented in Appendix A4.1. *t*-statistics are reported in parentheses *, **, *** indicate significance levels (two-sided) of 10%, 5% and 1%, respectively.

Appendices of Chapter 4

Appendix A4.1 Variable Definitions

Variables	Definition	Data Source
Ret	Monthly stock return following the month in which the forecast dispersion is measured.	Obtained from CRSP
Dis_nonGAAP	Dispersion in analysts' non-GAAP forecasts measured as the standard deviation of analysts' non-GAAP forecasts scaled by stock price at the end of the prior month.	Obtained from I/B/E/S
Dis_GAAP	Dispersion in analysts' GAAP forecasts measured as the standard deviation of analysts' GAAP forecasts scaled by stock price at the end of the prior month.	Obtained from I/B/E/S
Dis_Ex	Dispersion in analysts' forecast exclusions measured as the standard deviation of analysts' forecast exclusions scaled by stock price at the end of the prior month.	Obtained from I/B/E/S
Size	Total market value at the end of the prior fiscal year.	Obtained from Compustat
BTM	Book to market ratio calculated as book value divided by market value. Book value is the total stockholder's equity at the end of the prior fiscal year.	Obtained from Compustat
Meanadj	Analysts' average forecast exclusions calculated as mean value of forecast exclusions divided by stock price at the end of the prior month.	Obtained from I/B/E/S
Dis_nonGAAP_qr	The quintile rank of analyst' dispersion in non-GAAP forecast. Dispersion in analysts' non-GAAP forecasts is assigned into 5 quintiles, the quintile ranks are further scaled to a standardised quintile rank from 0 to 1	Obtained from I/B/E/S
Dis_GAAP_qr	The quintile rank of analyst' dispersion in GAAP forecast. Dispersion in analysts' GAAP forecasts is assigned into 5 quintiles, the quintile ranks are further scaled to a standardised quintile rank from 0 to 1	Obtained from I/B/E/S
Dis_Ex_qr	The quintile rank of analyst' dispersion in forecast exclusions. Dispersion in analysts' forecast exclusions is assigned into 5 quintiles, the quintile ranks are further scaled to a standardised quintile rank from 0 to 1	Obtained from I/B/E/S
Size_qr	The quintile rank of firm size. Size is assigned into 5 quintiles, and the quintile ranks are further scaled to a standardised quintile rank from 0 to 1.	Obtained from Compustat
BTM_qr	The quintile rank of book to market ration. Book to market ratio is assigned into 5 quintiles, and the quintile ranks are further scaled to a standardised quintile rank from 0	Obtained from Compustat

	to 1.	
Intangible	A dummy variable that takes the value of 1 if firms have intangible assets, and otherwise 0.	Obtained from Compustat
Mgr_Exl	A dummy variable that takes the value of 1 if manager reports exclusion earnings, and otherwise 0.	Obtained from Bentley et al. (2018) managers' non-GAAP earnings disclosures data set

Chapter 5

Conclusions

5.1 Summary of findings

The thesis seeks to assess the practical implications of equity analysts' non-GAAP and GAAP earnings reporting to different capital market participants. This starts by noting the analysts' disagreement on non-GAAP actual earnings measures and how this discrepancy affects past inferences on analysts' forecast rationality and overreaction (Chapter 2). Chapter 3 then analyses the links between non-GAAP and GAAP earnings surprises and stock market's short-term and long-term reaction in an international setting. Finally, I look at analysts' disagreement on GAAP earnings forecasts and forecast exclusions, and their relationship with future stock returns in the U.S. market in Chapter 4.

Chapter 2 examines analysts' actual and forecast GAAP and non-GAAP earnings per share (EPS) from a sample of analysts' reports for large European banks. In this chapter, I document significant variation among sell-side analysts' non-GAAP actual earnings measures. In contrast, this disagreement is not evident for GAAP actual earnings measures. This is interesting because prior assessments of analysts' forecast accuracy, informativeness and persistence of non-GAAP and GAAP measures are based on I/B/E/S, which reports a single actual non-GAAP earnings figure for each firm year. Using my unique dataset, I also find that analysts' forecasts appear more accurate and more biased compared to the results using I/B/E/S actuals. My findings support the argument that the GAAP system provides an important disciplining role that previous literature may have underestimated.

Chapter 3 studies the relative informativeness at the earnings announcement date and post earnings announcement drift (PEAD) associated with GAAP and Non-GAAP earnings surprises. Due to the unavailability of GAAP forecasts data before 2004, prior studies on the informativeness of different earnings definitions and PEAD calculate GAAP earnings surprise using the difference between GAAP actuals and non-GAAP forecasts. This measurement error problem has led to concerns about the comparability of the earnings metric and the potentially contaminated existing results. This chapter overcomes this issue by measuring GAAP earnings surprises as the difference between GAAP actuals and GAAP forecasts from I/B/E/S. My findings show that investors still perceive non-GAAP earnings to be more informative than GAAP earnings at the earnings announcement date. However, previously identified GAAP earnings surprises downwardly bias market responses to GAAP earnings. In addition, after correcting the measurement error, I find that the GAAP-based PEAD is higher than the non-GAAP based PEAD, indicating that investors may not use the information contained in GAAP earnings as efficient as non-GAAP earnings.

Chapter 4 studies analysts' disagreement on GAAP earnings forecasts, forecast exclusions and their relationship with future stock returns. Prior studies have established that dispersion in analysts' non-GAAP forecasts is negatively associated with stock returns but have often neglected GAAP forecasts on the grounds that they were unavailable on I/B/E/S until 2004. In this chapter, the non-GAAP forecasts are separated into two components: GAAP forecasts and exclusions forecasts. My results indicate that both analysts' disagreement on non-GAAP forecasts and disagreement on GAAP forecasts have a negative association with future stock return. Dispersion in analysts' GAAP forecasts seem to capture similar information as dispersion in non-GAAP forecasts, but it is a more appropriate measure of divergence of investors' opinion as GAAP forecasts are subject to less potential manipulation by analysts. However, a higher level of disagreement on forecast exclusions is associated with higher future stock returns. The results of the sub-sample tests suggest that dispersion in forecast exclusions reflects the firm idiosyncratic risk and the uncertainty of fundamental firm value. This chapter provides additional evidence on the implications of analysts' GAAP forecasts and forecast exclusions for capital market participants.

5.2 Limitations and Recommendation for Future Research

Like any research, this thesis is subject to certain limitations that researchers may consider when interpreting my results and designing new studies. First, in Chapter 2, I use manually collected data from analysts' reports. The sample consists of 4 UK banks and 5 European banks. Although I chose the banking sector on the grounds that it is very large, neglected in academic research terms and also economically important, this choice comes at the expense of generality. I therefore caution readers to interpret the results carefully when generalising to non-financial corporate sectors. Further research could determine the extent of disagreement between analysts about the actual earnings of less complex companies. Moreover, I am unable to ascertain whether analysts opportunistically adjust actual non-GAAP measures *ex post* to justify their earlier forecasts, or whether they try to signal their superior skills of processing accounting information through more extensive adjustments. Thus, future studies may also explore reasons why analysts report different actual non-GAAP EPS.

Secondly, in Chapter 3, whilst my dataset is extracted for an international sample consisting of firms from the UK and 10 Eurozone countries, it is still important to see the samples from other countries where different institutional environments may influence analysts' disclosure of non-GAAP financial measures. In addition, I only examine GAAP and non-GAAP earnings surprises in this chapter, so future research can investigate market reactions to alternative definitions of earnings surprises, such as those defined by the difference between managers' reported pro forma earnings and analysts' non-GAAP forecasts. Furthermore, future studies can also investigate how different institutional factors affect the short-term market reaction and long-term PEAD associated with GAAP and non-GAAP earnings surprises across these countries.

Finally, there are more interesting issues to be examined following the results reported in Chapter 4. In Chapter 4, the negative association between dispersion in GAAP forecasts and future stock returns can be ascribed to either information asymmetry or uncertainty. However, I do not fully differentiate which components explains the negative relationship between disagreements on analyst' GAAP forecasts and future stock returns. In addition, I find that dispersion in analysts' forecast exclusions are positively associated with future stock returns. Evidence suggests that this could be ascribed to the fundamental uncertainty risk about firm value. Future research may explore other explanations by separating analysts' forecast exclusions into special items (non-recurring components) and other exclusions (recurring components).